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Peer Effects and Ownership Costs in the Diffusion of Residential Solar Photovoltaic in California

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Peer Effects and Ownership Costs in the Diffusion of Residential Solar Photovoltaic in California

by

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Abstract

Peer Effects and Ownership Costs in the Diffusion of Residential Solar Photovoltaic in California

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This research analyses the California Solar Initiative (CSI) Program data to identify and describe peer effects and price elasticity to adoption affecting the patterns of residential PV adoption. Descriptive statistics and adoption trends are analyzed to explore the impacts of peer effects and third-party owned system on the diffusion of residential solar PV in California. As the residential solar PV technology is still in an early stage of market formation, understanding the patterns of adoption in relatively more mature market can have broad implications for wider diffusion of the technology at the national level.

In the first part of the thesis, I build an econometric model to estimate the influence of system cost and peer effects on the rate of diffusion at the zip code-level. The results reveal significant and positive installed base effects in the rate of future adoption. These results provide support to the hypothesis that peer effects help accelerate the adoption of new technologies. The cost-to-customer reduction is negative and

significant at the state level. The impact of installed base in inducing new adoption is larger in zip codes with higher overall adoptions.

The second part of the thesis presents trends in installation and choice of system capacity of major adoption clusters in California and analyzes the spread of third-party owned systems. Evidence from major adoption clusters in California has shown that growth in leasing adoption exhibits exponential characteristics while growth of customer owned system shows strongly linear feature. This suggests that third-party owned systems play a role in expanding the solar PV market to a significantly large population, especially given that this business would significantly reduces information cost associated with PV adoption.

These results offer direct policy and marketing insights that would be useful in speeding up the diffusion of residential PV.

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Chapter 1: Introduction

1.1 Motivations

The U.S. grid-tied photovoltaic (PV) capacity from the residential sector has increased from under 10 MW to over 150 MW between 2001 and 2009 (SEIA 2010). The growth, however, has been limited to relatively few states such as California, New Jersey, Arizona, and Colorado. The locations of U.S. residential PV markets exhibit cluster characteristics where, at the regional level, states with some combination of high electricity prices, good solar resources, and strong financial incentive schemes have a larger share of adopters relative to other states. There is a high disparity in installed capacity between the leading states and the rest of the country. According to the California Solar Statistics, the total installed capacity for residential PV system in that state is over 315 MW (CSI 2012) while states such as Nebraska, Virginia, and Kansas have less than 0.1 MW in total installed capacity (EERE 2010).

The disparity in installed capacity among the states can generally be explained by the availability of financial incentives programs and renewable energy policies in various states. However, clustering of adopters can also be seen at a localized level within the states and utility service territories. Evidence from the California Solar Initiative (CSI) Program shows that the diffusion of residential PV is disproportionally distributed within the states' boundaries where certain areas see more adopters of the technology than others. Figure 1.1 shows the heat map of CSI Program installation depicting the major clusters in the state.

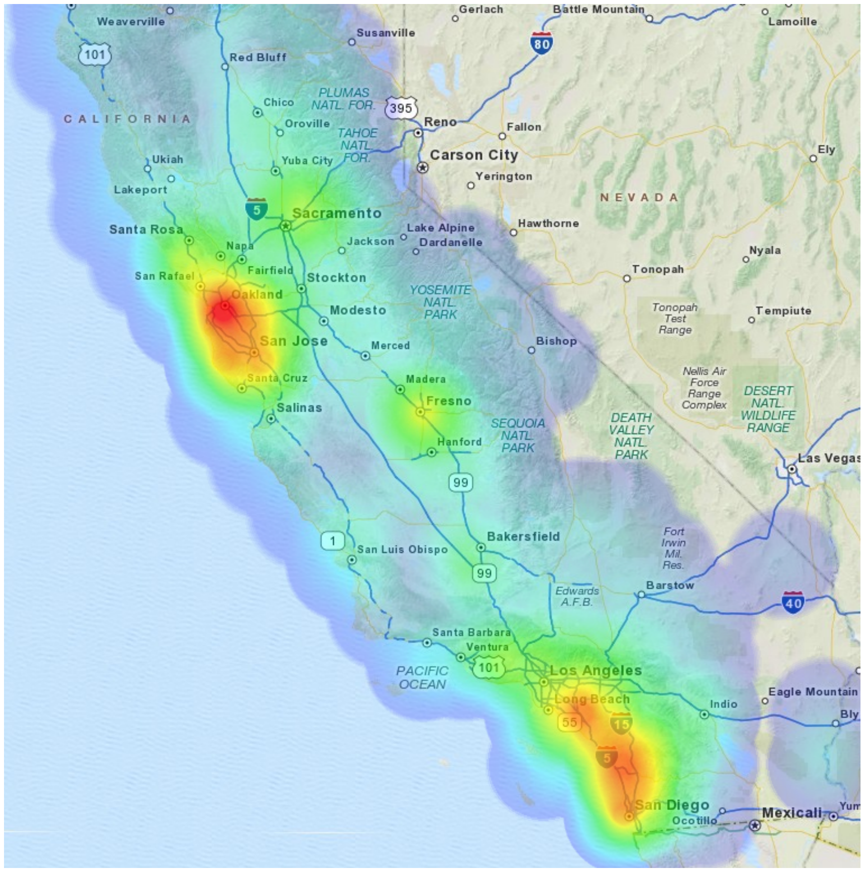

Figure 1.1: Heat map using system installation data from CSI program from 2007 to June 30, 2011 showing solar PV installation clusters in California

This research looks into the PV adoption data from the CSI Program to identify and describe some of the factors affecting the patterns of residential PV adoption based on spatial-temporal analysis. Empirically, what are the effects of installation cost and existing installed base on the rate of diffusion at the zip code-level. Particularly, I seek to understand the impacts of peer effects and third-party owned system on the diffusion of residential solar PV in California. California is the leader in residential PV installed capacity (Hoen *et. al*. 2011). As the technology is still in an early stage of market, formation, understanding the patterns of adoption in relatively more mature market like

California can have broad implications for wider diffusion of the technology at the national level. Identifying the factors influencing the diffusion of residential solar photovoltaic in California can provide policy makers and other stakeholders in other states some ideas of how the diffusion process might unfold so that they may design policy or marketing intervention to speed up the diffusion process.

1.2 Background and Data

1.2.1 Residential Solar PV Incentive Programs

There are incentive programs at different scales: federal, state, and city level. I provide two examples of incentive programs: one at the state level (CA) and the other at a city level (Austin) for which there is no state level incentive (TX).

California Solar Initiative

Following the "Million Solar Roofs Initiative" which set the goal of one million solar homes in California by 2015, the California Solar Initiative (CSI) was established by the California Public Utilities Commission in 2006. The $3.3 billion program was designed to greatly expand solar installation in California by 3,000 MW over ten years[2]. The CSI offers a solar rebate program to fund the installation of solar PV on existing buildings. The CSI collects all solar installation applications for the program incentive from three investor-owned utilities in the states: Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E). The three main utilities act as program administrators offering rebates to consumers. The California Public Utilities Commission oversees the CSI program. The main focus of the

[2] California Solar Initiative Annual Program Assessment, California Public Utilities Commission Go Solar California Report, June 2009

program is on residential and commercial scale installation. The CSI database includes commercial, residential, and non-profit installations.

Austin Energy Residential Solar PV Program

In 2003 Austin Energy issued a strategic plan that commits the city to one of the country's most ambitious renewable energy goal of achieving 20% renewable energy portfolio standard by 2020. The Austin city council proposed a strong focus on solar energy to achieve this goal. The plan calls for Austin Energy to commit to a solar rebate program for a minimum of ten years and to develop and implement what was the highest PV rebate level in the country. The initial budget for solar rebate program in fiscal year 2004 was set at $933,000. The program does not have a specified end date, but its budget is reassessed and approved on an annual basis at the end of fiscal year in October. Table 1.2 shows the historical budget allocations of Austin Energy solar rebate program for fiscal year 2004 – 2009. The 2003 strategic plan also sets initial solar generating capacity goals of 15MW by 2007, 30MW by 2010, 50MW by 2014 and 100MW of solar energy by 2020[3]. In March 2011, the goal was increased to 200MW by 2020.

Fiscal Year	Budget for solar PV rebates
2004	$933,000
2005	$2,000,000
2006	$3,000,000
2007	$3,180,000
2008	$3,000,000
2009	$4,500 ,000

Table 1.1: Austin Energy approved annual budget for solar PV rebate 2004-2009.

[3] Austin Energy Strategic Plan, December 4, 2003.

1.2.2 Residential Solar Photovoltaic Adoption Data

The CSI data is available publicly from the program's website; data on Austin's adoption was provided by Austin Energy. Analysis of Austin Energy data is limited to 773 residential PV systems that were installed from the start of the program in 2004 to the end of 2008. CSI data included in the analysis are from the system with completed installed date between 2007 through June 30, 2011. This includes 46188 residential systems. Both programs have commercial and residential components; in this thesis I focus on the analysis of residential adoption. Both California and Austin dataset contain technical characteristics of the system installed (e.g. system rating, inverter and solar panel type, and design factor), complete installation date, the total installed cost and the final rebate amount awarded.

1.2.3 Incentive Policies

California Solar Initiative

For residential customers, CSI Program rebates vary according to utility territory and system performance, which vary according to system size and other installation factors. There are two types of incentives on offered: expected performance-based buy down (EPBB) and performance-based incentive (PBI). The EPBB is an upfront incentive based on expected system performance. The rebate is paid in dollars/Watt based on system capacity. The PBI is a five-year monthly payment based on actual performance of the system. The PBI is paid on a fixed dollar/kWh of generation basis. Systems that are greater than 30kW in size are required to apply to the PBI scheme. Smaller system owners can elect to opt-in to the PBI scheme. Most residential systems are, however, under the EPBB scheme. Of the 46188 projects in the CSI database used analyzed in this thesis only 3 are PBI[4]. Figure 1.2 below shows the rebate "steps" schedule declining overtime based on the volume of solar megawatts (MW) with confirmed project reservations within utility service territories.

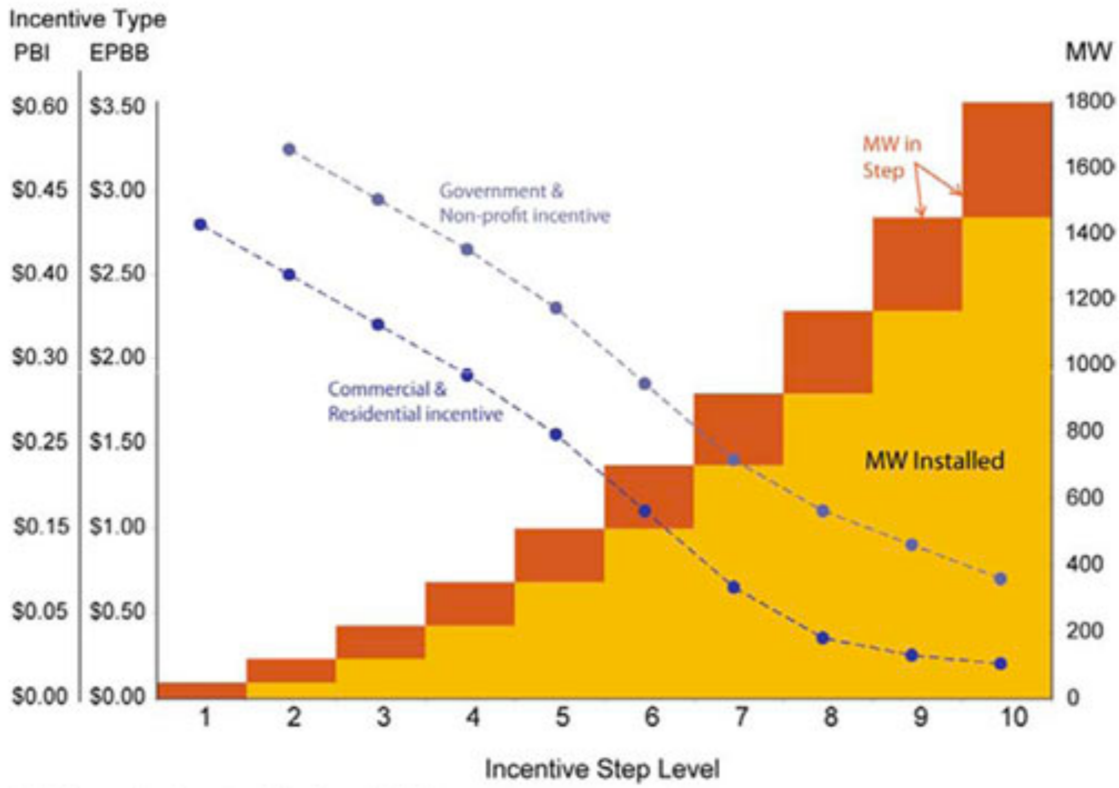

Figure 1.2: CSI Program rebate and MW allocation schedule.[5]

The rebate step assigned to system owner depends on the confirmed project reservation date, which does not necessary fall under one rebate step. As a result many system owners' total rebate payment were calculated based on two or more rebate steps.

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[4] Data includes residential projects that were installed as of June 30, 2011

[5] http://www.gosolarcalifornia.org/csi/rebates.php

Table 1.2 shows overtime the rebate level ($/Watt) for the three public utilities under the CSI program.

	Rebate Level ($/W)		
Date	**PGE**	**SCE**	**SDGE**
Jun-07	2.5	2.5	2.5
Sep-07	2.5	2.5	2.5
Dec-07	2.5	2.5	2.5
Mar-08	2.5	2.5	2.5
Jun-08	2.2	2.5	2.2
Sep-08	1.9	2.2	2.2
Dec-08	1.9	2.2	1.9
Mar-09	1.9	2.2	1.9
Jun-09	1.9	2.2	1.9
Sep-09	1.9	1.9	1.9
Dec-09	1.9	1.9	1.9
Mar-10	1.55	1.9	1.55
Jun-10	1.55	1.9	1.1
Sep-10	1.1	1.9	1.1
Dec-10	1.1	1.55	0.65
Mar-11	0.65	1.55	0.35
Jun-11	0.35	1.1	0.35

Table 1.2: CSI rebate ($/Watt) level history by quarter for three public utilities in California (data from 2007 – 30 June 2011).

Austin Energy Residential Solar PV Program

Similar to the CSI program, Austin Energy rebate was offered as an upfront incentive based on system capacity in $ per watt. This initial rebate offering of $5.00 per Watt was the highest PV rebate level in the country. The rebate amount is capped at $15,000 per annum and $50,000 lifetime limit. In 2009 Austin Energy changed the program scheme to performance-based incentive for commercial systems. Additionally, any systems installed in 2010 onward, residential households must meet a set of home energy efficiency requirements in order to qualify for a solar rebate. Austin Energy capacity based rebate level ($/Watt) from 2004 – 2008 are shown in Table 1.3.

Year	Rebate Level ($/Watt)
2004	$5.00
2005	$4.50
2006	$4.00 - $4.50
2007	$4.50
2008	$4.50

Table 1.3: Austin Energy annual rebate level ($/Watt) 2004 - 2008.[6]

Federal Investment Tax Credit

On top of the available incentives at the local or state level, residential solar PV owners can also apply for incentives offered by the federal government. The Energy Policy Act of 2005 provided a federal incentive for residential solar energy projects. The incentive came in the form of investment tax credit (ITC) of 30% of cost after accounting for local rebates with a $2000 cap on the total credit that can be claimed by a homeowner. The ITC was slated to run between January 1, 2006 and December 31, 2007 but was extended one additional year to December 31, 2008. The program was further expanded when the Energy Improvement and Extension Act of 2008 removed the $2000 cap for residential solar PV system that is placed in service after January 1, 2009. The Act also extended the ITC until December 31, 2016.

1.2.4 Installed System Cost

A survey conducted by Lawrence Berkley National Laboratory[7] (LBNL) found that the module costs represent about half of the total residential PV installed costs,

[6] Libby, L. Austin Energy Solar Programs. February 23, 2011. Presentation to University of Texas EST Group.

material, equipment, and inverter cost make up about 15%, labor represents about 10%, and overhead and regulatory compliance make up the remaining cost (Wiser 2009). At the project level installed system cost differs based on system size, equipment cost, and system design (such as number of inverters and battery-based system). Module price component is susceptible to global market fluctuations and, to an extent, affects system costs across markets. Installed system costs may differ across markets as a result of a variety of factors, including differences in: incentive policies; interconnection standards; labor costs; rebate application process, permitting, and local supply chain. A report by LBNL shows a wide range of average installed costs across twenty-two states for system smaller than 10kW with the lowest average cost of $6.3/W in New Hampshire to a high of $8.4/W in Utah. The reports found that the two leading PV markets, California and New Jersey, are not ranked among states with low-cost; instead, the lowest cost states are those with relatively small markets, which illustrate the importance of state and local factors in installed system costs (Wiser 2011).

National level data shows that from 1999-2010 the average installation cost of grid-connected solar PV systems declined by $4.5/W from $12.1/W to $7.6/W for systems that are less than 5kW and by $3.3/W for systems in the 5-10 kW in size (Wiser 2011). California Solar Initiative data also shows that the average system cost has decreased over time. Figure 1.3 shows the average system cost per Watt by quarter for CSI program.

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[7] LBNL published a series of reports under the title "Tracking the Sun" documenting the trends in installed costs of customer sited PV systems on a national level.

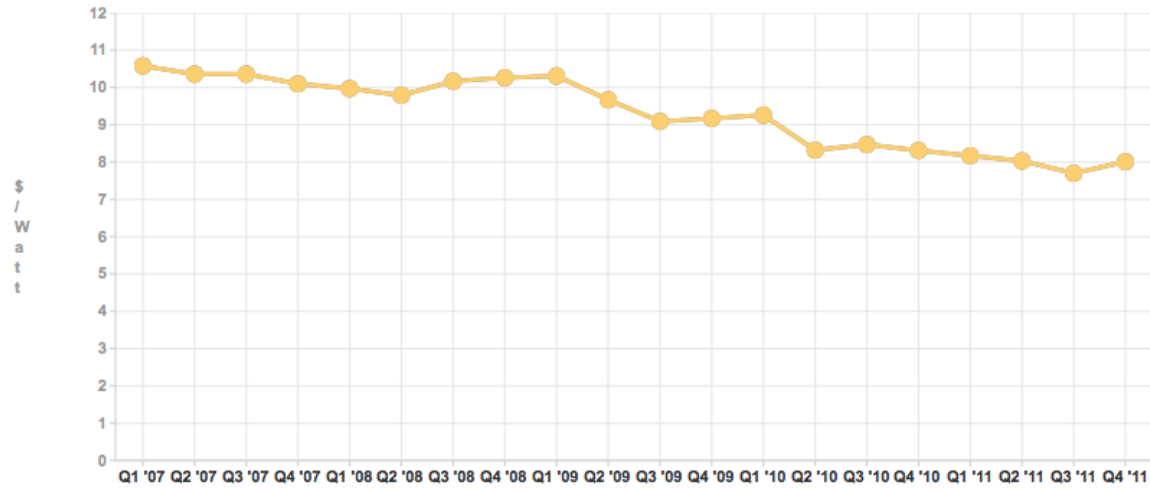


Figure 1.3: Average installed residential system cost ($/Watt) by quarter over the life of the CSI program[8]

1.2.5 Demographic Data

Annual demographic data from 2007 and 2009 were obtained from commercially available data produced by Environmental Systems Research Institutes (ESRI). The ESRI dataset represents a statistical estimate of population demographics at the ZIP code-level and includes data on population, age, household characteristics, income, and housing. Summary statistics for demographic data for 2007 and 2009 are shown in Appendix A.

1.3 Research Goals

This thesis is an attempt to understand and describe the role of peer effects and financial factors in influencing the rate of residential solar PV adoption in California. There are two main research goals. The first goal is to assess the influence of system cost and peer effects on the rate of diffusion at a zip code-level. Interpersonal networks (peer effects) is an important factor that influences an individual's decision to adopt a new

[8] http://www.californiasolarstatistics.org/reports/quarterly_cost_per_watt/

technology. Adoption decision depends on the information received from previous adopters within the same interpersonal network. Peer effects play a role in the diffusion process by spreading information and influencing opinions about new technology. Controlling for the differences among zip codes, I create an econometric model to estimate the future adoption rate based on cost-to-consumer and existing cumulative installed capacity, which is a proxy for peer effects.

The second goal is to analyze the trends in installation, particularly on the spread of third-party owned systems. By analyzing the adoption of residence owned and third-party own systems (i.e. leased) in six major adoption clusters, I construct descriptive statistics of each cluster and attempt to provide some generalizations about market expansion as a result of third-party owned business model.

1.4 Structure of the Thesis

The thesis is divided into five chapters. The next chapter presents literature review of diffusion modeling and theories. In Chapter 3 I present an econometric model quantifying the effects of installed-base and system costs on the rate of adoption. In Chapter 4 I perform cluster analysis of major adoption areas in California and present trends and adoption analysis of customer and third-party owned systems. Chapter 5 concludes the thesis with discussion and suggested areas for further research.

Chapter 2: Literature Review

Much research attention has been given to explain the process of technology diffusion. Early literature and research on the subject were generally presented in a descriptive manner. Overtime, analytical models were developed to test the theories against empirical data. This chapter presents a brief overview of the most popular frameworks for constructing diffusion models as well as provides a discussion on some of the important factors in the diffusion of new technologies.

2.1 TECHNOLOGY DIFFUSION MODELS

The technology s-curve is one of the most widely used models to forecast technology diffusion. The s-curve theory states that in early stage, the rate of technology adoption is relatively slow. The rate of diffusion increases as more people adopt the technology. As the market begins to mature, the rate of adoption decreases and finally plateaus as the market saturates. Figure 2.1 shows the technology diffusion s-curve over time. While a symmetric S-curve is rarely observed in the actual diffusion of a technology the S-curve provides a useful framework for studying the diffusion process.

Two most common models used to describe technology diffusion process are epidemic model and probit model (Geroski 2000). The epidemic model is based on the spread of knowledge and information about the new technology. Under the epidemic model the reason why some consumer adopt new technologies later than other is that they found out about the innovation later than the earlier adopters. Therefore, the likelihood of adoption is a function of time and the rate of information spread from a source. The probit model assesses the adoption decision based from the adopter's perspective. The probit model takes individual's goals, capabilities, and believes into account whereas the epidemic model focuses on the rate of information diffusion (Geroski 2000). This thesis examines the diffusion of residential solar PV from both perspectives. The epidemic framework is used to understand the role of peer effects on the spread of the technology while the probit model framework is used to understand the adoption decision from the customer financial standpoint.

2.2 INNOVATIVENESS, ADOPTER CLASSES AND CHARACTERISTICS OF EARLY ADOPTERS

Innovativeness is defined as the degree in which an individual is relatively earlier in adopting new ideas than the other members of the society. Adopters of new technology can be divided into five different classes: innovators, early adopters, early majority, late majority, and laggards. The theory suggests that these different classes of adopters follow a normal distribution curve.

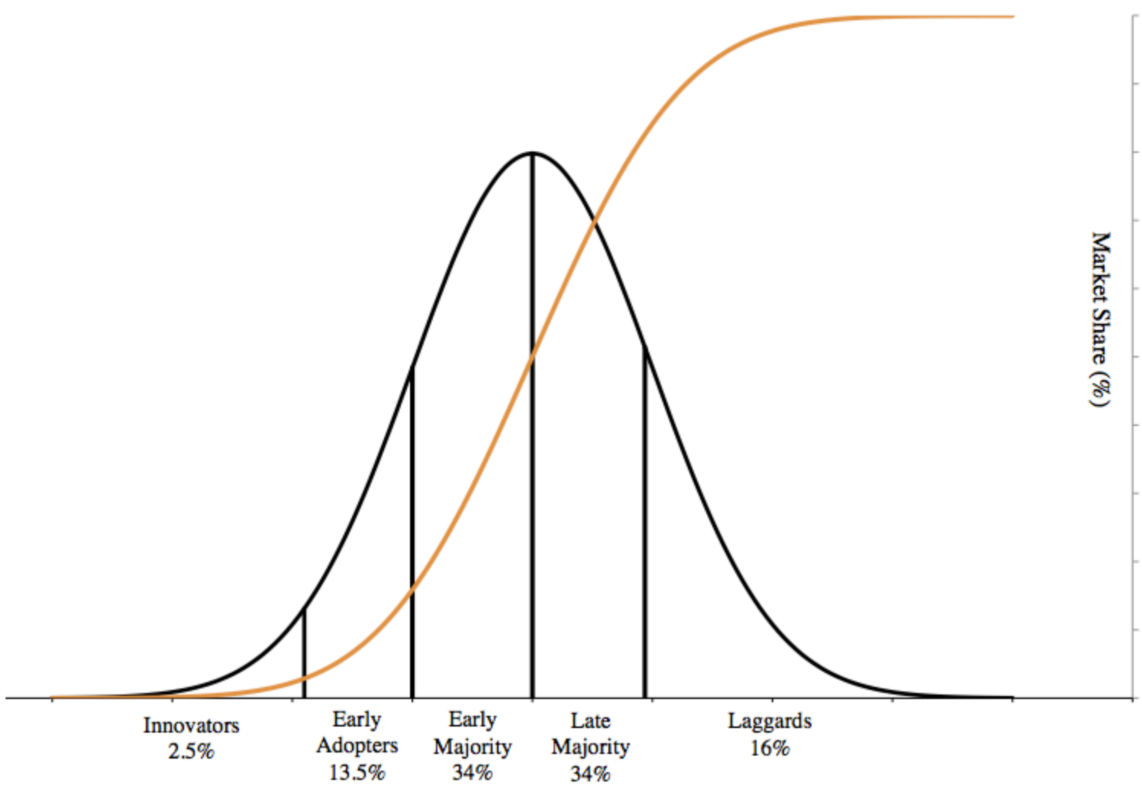


Figure 2.1: Roger's five adopter classes and technology s-curve

The adopter classes are determined by their differences in socioeconomic status, risk aversion, and opinion leadership (Rogers 2003). Therefore, successful growth of the new technology will depend on the transition niche market that appeal to innovators class to one in which the early and late majority adopter classes will accept. The transition through these consumer classes also depends on other complementary factors such as knowledge about the technology, local suppliers, perceived value, attitudes, and interpersonal and social networks (Stern 2000).

According to Rogers, indicators of early adopters and innovativeness fall under three broad categories: socio-demographic, personality values, and communication behavior. In socio-demographic terms, they tend to have higher social status, education, and degree of social upward mobility. Socio-demographic variables associated with adoption of solar energy technology have been documented in various studies (Durham 1988, Faiers *et. al* 2006, McEachern 2008, Rothfield 2010).

Schelly (2010) modeled residential solar thermal adoption in the United States based on three indexes: socio-economic, environmental concerns, and ecological (e.g. insolation). The study found that socio-economic index was the most robust predictor of solar thermal technology adoption where areas with higher education levels, low unemployment rate, and higher levels of disposable income are more likely to have more adopters. Specific to residential solar PV in California, Rothfield (2010) estimated the likelihood of adoption based on consumer characteristics, electricity rates, and the number of previous installed systems in a given ZIP code using a probit model. Drury (2012) found correlations between population socio-demographic characteristics and the decision to adopt third-party owned solar PV systems in southern California.

Personality values have not been as widely studies due to difficulties in measuring more abstract variables associated with innovativeness such as intelligence, the ability to empathize, attitude toward change, and risk tolerant. Communication behaviors such as social participation, interconnectedness, and opinion leadership are also difficult to quantify especially with non-individual assessment level.

2.3 CONTEXTUAL FACTORS, INFORMATION NETWORKS AND PEER EFFECTS

In addition to intrinsic consumer characteristics, the decision to adopt also depends on contextual factors. The attitude, context, and behavior theory indicates that personal behaviors are more strongly influenced by context than by attitudes or believes. The attitude-behavior association is strongest when contextual factors are neutral. On the other hand, when the contextual factors are strongly positive or negative the attitude factors on behavior have little impacts (Stern 2000). For example, when a household decides to make the decision to installed solar PV the contextual factors such as electricity price, available incentives, and ease of finding qualified contractors play a more important role than personal environmental concerns. Presumably, where the number of adopters is high, the contextual factors associated with adopting the technology are positive.

Two broad contextual factors explored in this thesis are financial and information. Financial consideration plays an important role in consumer's decision to adopt. Faiers (2006) found that if consumers do not feel solar technology is superior to their current sources of power they are unlikely to adopt based on financial and economic considerations. A study conducted by National Renewable Energy Lab (NREL 2009) calculates the break-even cost[9] for residential PV adoption for utilities service areas in the United States where residents in areas with low break-even cost would be less likely to adopt the technology due to longer payback time in the investment. The study found that

9 Break-even cost is define as the point where the cost of PV-generated electricity equals to electricity from the grid, as a function of electricity price, financing, solar resources, electricity rate structure, and available incentives.

customers in states with a combination of high electricity prices and good solar resources (e.g. CA and HI) and states with a combination of high electricity prices and incentives (e.g. NJ and MA) will be at break-even cost given the installed cost of approximately \$8/W. However, the study also noted that the presence of break-even conditions does not necessary equate to large consumer adoption of the technology. Benthem (2007) model the economic efficiency of the CSI subsidy policy using consumer choice, learning-by-doing and environmental externalities as key parameters. For consumer choice characteristics they model the diffusion using an S-shape demand curve as a function of consumer net present value and diffusion process using logistic growth function to model diffusion adjusted each year by the amount of previous year's adoption.

Although, the financial considerations greatly affect the decision to adopt, social and communication networks are also key determinants in the actions of individuals who make up the technological system. Social interactions between previous and potential adopters create information networks around the technology that results in peer effects. The central assumption of peer effects is that technology diffusion is related to the number of previous adopters. Beyond introducing new technology to potential adopters, peer effects may increase the speed of diffusion by lowering uncertainties associated with new technologies.

An important barrier to adoption is the uncertainty over the performance of solar PV technology. If the performance of residential PV system is uncertain, then potential adopters will perceive the risks associated with owning the system to be high. According to Rogers (2003), people rely on the personal evaluation of the technology by those who already adopted. As more people become adopters the observed performance of the technology will spread through the networks at a faster pace and further reduce the uncertainties associated with owning the technology. This social learning process and knowledge spillovers reduce the costs and uncertainties associated with residential PV technology. The theories on the diffusion of innovation suggest that technology adoption (such as the decision to install solar PV) decision is a social process that is influenced by previous adopter through interpersonal network exchanges. As such, the diffusion of residential solar PV should exhibit some evidence of information network and peer effects.

A number of previous studies on modeling technology adoption have made explicit the roles of peer effects in the diffusion process. Two of the most recent studies: Narayanan and Nair (2011) measured the peer effects on the sale of hybrid vehicle in California using the number of previous adopters. Bollinger and Gillingham (2011) identified causal peer effects in the diffusion of solar PV in California using a first-differenced hazard rate model.

Chapter 3: Peer Effects and Cost Factors in Solar PV Diffusion

This chapter explores the effects of peer influences, financial incentives and system cost on the technology adoption rate. Cumulative installed base is used as a proxy for peer effects – the higher the installed base the more the impact of peer effects will be. I model the rate of residential PV adoption in each zip code based on the cost-to-customer and the previous cumulative installed capacity and estimate the effects of the two variables on new residential PV adoption in California. I also determine whether the effects of cost-to-customer and installed base operate differently for zip codes with high adoption (installed capacity) and whether these effects change over time. Lastly, I test the robustness of the model using geographical variations within California and Austin Energy dataset.

3.1 Methodology

3.1.1 Model Specification

Spatial analysis of the diffusion rate is limited by the available data. The analysis is at the zip-code level because it's the lowest spatial resolution in the CSI program data. As the diffusion profile has strong local characteristics due to factors such as installers, potential peer effects and targeted marketing activities by solar companies. Additionally, each zip code has different intrinsic characteristics that cannot be observed given the limitation of the dataset. Some unobserved heterogeneities include socio-demographic characteristics, local government effort to promote residential PV, energy conservation or sustainability practice, the present of opinion leaders who advocate PV adoption, and the establishment of qualified of local vendors. I use zip code fixed effects model for the analysis because it provides insights on individual zip code's technology diffusion path by allowing for the control for these zip-specific heterogeneities across time; thus, the model removes those effects and assesses the net effects of the independent variables (in this case cost-to-customer and cumulative installed capacity). Random effects model involving cumulative installed capacity would suffer from misspecification bias since it assumes independent and identically distributed unobservables that are uncorrelated with installed-based (Narayanan and Nair 2011).

3.1.2 Technology Adoption Rate

The rate of adoption is the relative speed with which members of a social system adopt an innovation (Rogers 2003). In diffusion research it is generally measured as the number of individuals who adopt an innovation in a given period. For solar photovoltaic, the cumulative installed capacity is generally used as the measure for technology diffusion (Shum and Watanabe 2007, Hart, 2009, Rothfield 2010). Following this convention, I model diffusion using cumulative installed capacity and technology adoption rate using installed capacity (Watt), not by the number of adopters.

Further, since there are variations in zip code population, it is necessary to normalize the rate of adoption to control for difference in population. In this thesis technology adoption rate is defined as the total capacity installed in a given zip code in one month normalized by the zip code's population density.

The number of owner occupied household was selected as the normalization variable as it is likely that the majority of PV installed are in owner occupied single-family housing unit, the decision to adopt would be made on a household, not individual, basis and any financial costs and benefits would be calculated as such. Zip codes where number of owner occupied household data is zero or unavailable were excluded from the model since the technology adoption rate cannot be normalized. Zip codes that had only one adoption data were excluded from the model due to SAS proc panel procedure limitations (SAS was the computational package used for estimating the models). This resulted in 1080 zip codes included in the analysis of the CSI data from 2007 to 30 June 2011. Figure 3.1 shows the normalized technology adoption rate by zip code from 2007 to 30 June 2011.

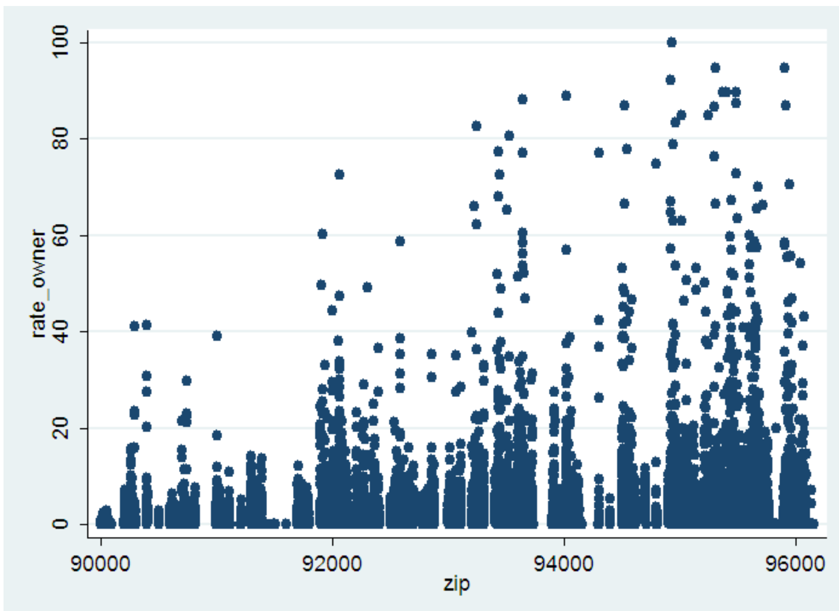


Figure 3.1 Technology adoption rate normalized by owner occupied household by ZIP code, excluding ZIP codes with technology adoption rate above 100 due to low population density.

3.1.3 Installed base

Cumulative installed capacity is defined as the total installed capacity based on CSI rating in a zip code up to the current month:

$$Q_{(i,M)} = \sum_{m=1}^{M} \sum_{n=1}^{N} q_{i,m,n}$$

where N is the total number of system installed in month m and $q_{i,n}$ is the system capacity (W) installed in zip code i.

The model assumes that the peer effect resulting from adoption start operating once installations are completed and continue to do so in the future periods (Bollinger and Gillingham 2011, Iyenger *et al*. 2011). In the analysis a lag time of three months, $Q_{(i,m-3)}$, is used as explanatory variable for cumulative capacity[10].

There are several reasons to use lag term. First, it addresses the endogeneity problem. Endogeneity arises when an explanatory variable is correlated with the error term. As the installed base in a given period may be correlated with unobserved errors, the regression may be bias. Using a lagged term for installed base address this problem by shifting the explanatory term so that its correlation with the error term is not contemporaneous. While adoption decision is influence by existing installed base, it is unlikely to be made contemporaneously with the newest installed system. For example, learning by observation of increase number of PV systems may play a role in decision to adopt but it is not sufficient. Interpersonal communications are needed in order to reduce technology risks and performance uncertainties for potential adopters. Moreover, the effects of cumulative installed capacity should have no immediate effect on the next month's installations due to the long lead-time for system installation. Therefore, a lag term is necessary in order to capture the difference between decision-making to when actual system is installed on a residence. Lastly, the lag time between existing stock and new installation should also prevented autocorrelation between the error term and the

[10] The median lag time between first confirmed reservation and completed date for CSI data is 4 months.

installed base explanatory variable if the duration of any autocorrelation in the errors is less than the lag time of three months[11].

3.1.4 Cost-to-Customer

Recognizing that cost variable is multivariate and endogenous this study adopted a simple cost-to-customer calculation based on system size, total cost and available incentives. Project installation cost varies by material cost, labor cost and system design, which include system size, number of inverters, whether batteries were installed, and types of panel. As the CSI database and data provided by Austin Energy do not have sufficient details to capture these variations, total project cost is used in the analysis. At the zip code level, cost reduction may vary due to contractor's installation experience and available supply chain infrastructure. For example, areas with high adoption rate the cost of installation may decrease more rapidly due to learning-by-doing and competitions between the installers[12].

The cost-to-customer analysis considers two incentive programs: the local rebate program and the federal investment tax credit. Cost-to-customer is calculated on a $ per Watt basis by dividing the difference in total cost and incentives by system size (Watt). The amount of local rebate and total system cost for each project is reported in the CSI database and Austin Energy dataset. For all systems, full federal investment tax credit was assumed; for systems installed between January 1, 2006 – December 31, 2008 the ITC of $2000 was used, 30% ITC of total system cost is used for systems installed after January 1, 2009. There were no federal investment tax credits for systems installed prior

[11] In their model Bollinger & Gillingham (2011) used completion date as explanatory variable and request installation date as the dependent variable to address the autocorrelation problem.
[12] Benthem, Gillingham, and Sweeney (2007) modeled the efficiency of CSI incentive structure based on the effects of learning-by-doing.

to 2006 (This is applicable only to data from Austin Energy, which goes as far back as 2004).

Cost-to-customer prior to January 1, 2006 ($/W) = [(total cost – local rebate)]/system size (W)

Cost-to-customer 2006 – 2008 ($/W) = [(total cost – local rebate) – $2000 ITC] / systems size (W)

Cost-to-customer after January 1, 2009 ($/W) = [(total cost – local rebate) * 0.7] / system size (W)

3.1.5 Level of Aggregation

The data is aggregated spatially at the zip code level. Zip code was used as the unit level analysis for the cross-sectional dimension because it is the finest spatial resolution available publicly through the CSI project database.

Technology adoption rate and installed capacity are aggregated at the monthly level. As the residential solar installations were growing at a very rapid rate in California, yearly and quarterly aggregation of installations may not provide sufficient detail information on the adoption rate given how time varying factors such as rebate rate, cumulative installed capacity, and effects of communication networks may influence the adoption rate. By increasing the time series component of panel data, monthly time aggregation account for the rapid rise in cumulative installed capacity while also improving the efficiency of the models' estimates. As most zip codes do not gain new adopters every month, the panel data is unbalanced.

For cost-to-customer data, I calculated the average cost based on the number of adopters in a given zip codes per quarter.

$$C_{(i,q)} = \frac{\sum_{n=1}^{N} c_{i,n}}{N_{i,q}}$$

Where N is the total number of system installed in quarter q and $c_{i,n}$ is the cost-to-customer ($/W) for each system installed in zip code i.

The cost-to-customer is aggregated to zip code–quarter level due to possible collinearity with the monthly installed capacity (Narayanan and Nair 2011). Local marketing and sale efforts can change both the cost and new installations during the marketing campaign. For example, a contractor may negotiate lower installation cost for customers in the same neighborhood resulting in lower cost-to-customer and higher new installations for that month. Aggregating cost-to-customer at quarter level assumes that marketing factors vary between quarters but not within quarters (Narayanan and Nair 2011) and that any effects resulting from changes in system cost do not immediately translate into new installation in the next month.

3.1.6 Models

The impact of installed base on the rate of adoption varies depending on several factors such as increasing demand over time, market size and saturation, and clustering of adoption. As these factors cannot be fully controlled in a model, model specification must reflect the underlying assumption of how installed base impact the rate of adoption overtime. Here I present two models with different assumptions on how the installed base (peer effects) can impact the rate of adoption at a zip code level. Model 1 represents the assumption of constant marginal impact of peer effects as cumulative installed capacity increases. Model 2 assumes increasing impacts of installed base on the rate of adoption.

Using zip code fixed effects specification and controlling for cost-to-customer and installed base, new monthly installed capacity in any given zip code can be modeled by:

Model 1:

$$\log(TAR_{(i,m)}+0.000001) = I_{i,m} + \beta C_{(i,q)} + \delta^{*}\log(Q_{(i,m-3)}+ 0.0000001) + \varepsilon_{i,m} \qquad (3.1)$$

Model 2:

$$\log(TAR_{(i,m)}) = I_{i,m} + \beta C_{(i,q)} + \delta^{*}Q_{(i,m-3)} + \varepsilon_{i,m} \qquad (3.2)$$

where I_i is the intercept for zip code i in month m

$TAR_{(i,,m)}$ is the normalized rate of PV adoption of zip code i in month m

$C_{(i,q)}$ is the average cost-to-customer installed in zip code i and quarter q

$Q_{(i,m-3)}$ is normalized total installed capacity in zip code i up to month m-3

$\varepsilon_{i,m}$ is the error term

β and δ are parameters to be estimated

For model 1, the assumption of existing installed base constant marginal effects on new adoption is captured by the log specification on cumulative installed base term (Bollinger and Gillingham 2011). A small number (0.0000001) is added to the installed base term to avoid log error for the early months when cumulative installed capacity is zero.

As the data shows that there are variations in zip code-level cumulative installed capacity, I test to see whether the effects of cost-to-customer and installed base operate similarly within zip codes that experience high level of adoption. In order to test this, zip codes are divided into two categories, high-zips and rest-of-market. Zip codes with the highest absolute installed capacity are defined as "high zips"; the remaining zip codes are defined as "rest-of-market." There are 1080 zip codes included in the CSI analysis and high zip codes are selected based on the their overall rank in the CSI program; for example, high-zips defined at the top 5% level would include the top 54 zip codes with highest cumulative installed capacity as of June 30, 2011 and the rest-of-market would include the remaining 1026 zip codes. I chose absolute cumulative installed capacity instead of cumulative installed capacity normalized by population as the measure of adoption level because normalized capacity can be skewed by zip codes with very low number of owner occupied household. A binary variable, *Z*, was created to represent high-zips where *Z* equals 1 for zip codes defined as high-zips and zero for the rest-of-market zip codes. The high zip code dummy term is interacted with cost-to-customer and installed base variable to determine whether there are statistically significant differences between the two groups.

Interaction terms to control for high-zips and rest-of-market zip codes differences are included to both models as:

Model 1:

$$\log(TAR_{(i,m)}) = I_{im} + \beta C_{(i,q)} + \delta \log(Q_{(i,m\text{-}3)} + 0.0000001) + \varepsilon_{I,m} + C_{(i,q)}{*}Z + \log(Q_{(i,m\text{-}3)} + 0.0000001){*}Z \tag{3.3}$$

Model 2:

$$\log(TAR_{(i,m)}) = I_{im} + \beta C_{(i,q)} + \delta Q_{(i,m\text{-}3)} + \varepsilon_{I,m} + C_{(i,q)}{*}Z + Q_{(i,m\text{-}3)}{*}Z \tag{3.4}$$

3.2 RESULTS

Table 3.1 presents the results for zip code fixed effects models. Both models show significant negative coefficient for cost-to-customer and significant positive coefficient for installed base.

	Model 1		Model 2	
	Estimate	Pr > |t|	Estimate	Pr > |t|
Cost-to-customer	-0.08691	<.0001	-0.09012	<.0001
Installed base	0.011938	<.0001	0.0033	<.0001
R-Square	0.6221		0.6216	

Table 3.1: Results for zip code fixed effects models. Parameter estimates for cost-to-customer are for quarterly cost. Parameter estimate for Model 1 installed base is for log(normalized cumulative installed capacity + 0.0001). Parameter estimate for Model 2 installed base is for normalized cumulative installed capacity.

Model 1

The coefficient estimate of -0.08691 implies that every \$1/W quarterly decrease in average cost-to-customer in a quarter leads to approximately 0.09% of the current cost-to-customer increase in new installed capacity in the next month from the previous month's adoption rate. This means that the impact of cost-to-customer reduction is higher for higher costs (i.e. impact of cost reduction if higher when cost reduces from \$7/W to \$6/W than from \$5/W to \$4/W). For example, if the average cost-to-customer between January – March decreased by \$1/W, the rate of adoption in April would increase by approximately 0.09% over March's adoption.

For zip specific installed base, the model shows significant positive coefficient for installed base of 0.011, which translates into an increase of approximately 0.011% for every 1% increase per owner occupied household installed capacity increase in a respective zip code. This means that if cumulative installed capacity in January were 1% higher, that would lead to a 0.011% increase in the rate of adoption in April from the previous month's adoption rate. For example, if the rate of adoption in March were 10 W per household, the April's rate of adoption resulting from a 1% increase in cumulative installed capacity in January would be nearly 10.0011 W per household.

Model 2

The impacts of decreasing cost-to-customer for both models are similar. Estimate for model 2 shows that a $1/W quarterly decrease leads to approximately 0.094% increase in the rate of adoption. The estimate impact of installed base on the rate of adoption for Model 2 is 0.0033. Due to the assumption of increasing effects of installed base, the change in the rate of adoption based on a 1% increase in installed base is 0.33% of the cumulative installed capacity not the previous rate of adoption as in Model 1. For example, suppose that cumulative installed capacity for a zip code in January is 101 W per household (an increase of 1% from 100 W per household in the base case scenario in January) the rate of adoption for the month of April would increase by 0.333 W[13] per household from the rate of adoption in March.

The results of these two models represent two extreme of the assumption of how installed base may impact the rate of adoption. As such the actual magnitude of peer effects as estimated by zip code fixed effects is somewhere in between these two model estimates[14].

[13] The change in adoption rate is a function of cumulative installed capacity multiply by the coefficient estimate for installed base.

[14] The models also do not account for certain correlated unobservables that could affect the rate of adoption such as localized marketing campaigns. Refer to Bollinger & Gillingham (2011). Peer Effects in the Diffusion of Solar Photovoltaic Panels for a study that address the issue using zip-quarter fixed effects. Using the same data from CSI database and zip code quarter fixed effects specification; the study found that a 1% increase in the zip code's installed base increases the adoption rate by approximately 1%.

Table 3.2 and 3.3 shows the results of the dummy interaction terms model for Model 1 (Equation 3.3) and Model 2 (Equation 3.4).

Variables	Estimate	Pr > |t|	Estimate	Pr > |t|
cost-to-customer	-0.06178	<.0001	-0.05796	<.0001
installed base	0.017172	0.0003	0.013944	<.0001
installed base - high zips	0.035785	<.0001	0.033216	<.0001
cost-to-customer - high zips	-0.01721	0.0009	-0.03256	<.0001
R-square	0.6337		0.636	
High zips definition	High zips = top 50		High zips = top 100	

Table 3.2: Results for Model 1 (Equation 3.3) using top 50 and top 100 as high zip codes.

Variables	Estimate	Pr > |t|	Estimate	Pr > |t|
cost-to-customer	-0.10909	<.0001	-0.09647	<.0001
installed base	0.182661	<.0001	0.178922	<.0001
installed base - high zips	0.006292	<.0001	0.23586	<.0001
cost-to-customer - high zips	0.006412	0.5994	0.037425	0.0004
R-square	0.6322		0.6392	
High zips definition	High zips = top 50		High zips = top 100	

Table 3.3: Results for Model 2 (Equation 3.4) using top 50 and top 100 as high zip codes.

Both models results show that differences between cost-to-customer for high zips and rest-of-market are statistically significant for high zip codes defined as top 100 zip codes with highest installed capacity. Interaction term for cumulative capacity are significant for both top 50 and top 100 zip codes models.

Model 1 and 2 points to different effect of cost-to-customer between high and low adoption zip codes. For Model 1, the coefficient for cost-to-customer interaction term is negative and significant. This means that customers in high installation zip codes adopt the technology at lower cost than those in low adoption zip codes. Conversely, the coefficient for the cost-to-customer interaction term for Model 2 is positive suggesting that high zip code customers tend to install system at higher average cost for model that includes the 100 top zip codes but is not significant for the top 50 zip codes. This result does not make sense as the difference between the top 50 zip codes and the rest of the market should be more prominent than the difference between the top 100 zip codes and the rest of the market. Therefore, if the model for the top 50 zip codes show insignificant difference from the rest of the market, it is unlikely that there is a significant difference between the top 100 zip codes and the rest of the market. While the effect of decreasing cost-to-customer on increasing the overall adoption rate is consistent across all models, it is inconclusive whether the there is systematic difference in the cost-to-customer between zip codes with the highest adoption level and the rest of the market due to the inconsistency of results as discussed above.

Although the two models provide divergent results for cost-to-customer differences, the coefficients for high zip-installed base interaction term are positive and significant for both models. To get a better sense of how the effects of installed base may vary among zip codes, I ran a successive series of models to compare the installed base coefficient estimates for high adoption zip codes and low adoption zip codes. Instead of using dummy variables to determine whether there are statistically differences, I separate the data set into to two models: high zips and rest-of-market. High zips models include only zip codes that are classified as having high adoption; the remaining zip codes are included in rest-of-market models. Table 3.4 and Table 3.5 compares installation base estimation results for high adoption zip codes and rest-of-market models for Model 1 and 2.

Installed Base Estimates	High installed capacity ZIPs	Rest of Market
Top 1%	0.059406	0.011171
Top 2%	0.056233	0.011171
Top 3%	0.048166	0.010207
Top 4%	0.044316	0.009859
Top 5%	0.046505	0.00911
Top 10%	0.011937	0.006906

Table 3.4: Installed base parameter estimates results comparison between high zip codes and rest-of-market models for Model 1.

Installed Base Estimates	High installed capacity ZIPs	Rest of Market
Top 1%	0.005868	0.003043
Top 2%	0.008101	0.002526
Top 3%	0.008278	0.002295
Top 4%	0.007834	0.002208
Top 5%	0.008154	0.001863
Top 10%	0.0033	0.000982

Table 3.5: Installed base parameter estimates results comparison between high zip codes and rest-of-market models for Model 2.

All models show significant positive coefficient for the installed base. The coefficient estimates for the top tier zip codes are higher than rest-of-market models suggesting higher social connectivity within these zip codes.

3.3 Robustness Check

In this section, I conducted a set of robustness checks for the model. The first set of tests leverage the richness of CSI data by varying the geographical granularity of the analysis. I modeled subsets of CSI data at different levels of geographical boundary. The premise for this is installed base effects get weaker as the geographical boundary of analysis expands. I ran a set of models at the utility, county, and city levels using the same methodology as the entire state model. The estimates are reported in Table 3.6.

	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|
Cost-to-customer	-0.06977	<.0001	-0.08257	<.0001	-0.0756	0.0275
Installed based	0.012384	<.0001	0.019638	<.0001	0.027822	<.0001
Geography	PG&E		Santa Clara County		San Jose	
Number of zip codes	597		51		29	
R-Square	0.6536		0.4885		0.4557	

	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|
Cost-to-customer	-0.11571	<.0001	-0.13492	<.0001	-0.08547	0.129
Installed based	0.007264	<.0001	0.016567	<.0001	0.027871	0.0058
Geography	SCE		Orange County		Huntington Beach	
Number of zip codes	405		80		4	
R-Square	0.5251		0.4659		0.1337	

	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|
Cost-to-customer	-0.13411	<.0001	-0.1394	<.0001	-0.16087	<.0001
Installed based	0.022831	<.0001	0.023698	<.0001	0.024619	<.0001
Geography	SDGE		San Diego County		San Diego	
Number of zip codes	104		91		42	
R-Square	0.5389		0.5422		0.5115	

Table 3.6: Parameter estimates results for utility, county, and city level models for Model 1. The top part of the Table shows robustness test for the PG&E territory. The middle part of the table shows robustness test for SCE territory. The bottom part of the Table shows robustness test for SDG&E territory.

The results in Table 3.6 replicate the analysis in Model 1 (Equation 3.1) but with smaller geographical boundaries. The rational for running the model at successively smaller geographical boundary is to test the estimate of installed base. As peer effects operates at a local level, it is expected that model that includes smaller geographical areas would produce higher coefficient estimate for installed base than models that cover larger area. In other words, peer effects should become stronger as we reduce our area of analysis. As shows in Table 3.6 above the coefficient estimates for installed base increase as the geographical areas decrease (from left column to right column).

Cities included in Table 3.6 are those with relatively higher cumulative installed capacity. It is likely that the models consisting of cities with few adoptions will produce lower estimates. I selected cities with high adoption for this analysis in order to support earlier finding that installed base effects are greater in high adopter zip codes. Results reported in Table 3.4 and 3.5 above have already provided evidence to this hypothesis. Results from models at city level further point to higher peer effects within these communities.

Table 3.7 reports the second robustness check using independent data set from Austin Energy.

	Estimate	Error	t Value	Pr > |t|	R-Square
Cost-to-customer	-0.03956	0.0108	-3.67	0.0003	
Log installed base (3 months lag)	0.006994	0.00306	2.28	0.0229	0.5635

Table 3.7: Parameter estimates results for all Austin data

Replicating the methodology and analysis from CSI models, the result is presented in Table 3.7. Estimate results from the Austin model compare favorably with estimates from CSI models. The cost-to-customer show negative significant relationship with rate of adoption. Significant positive coefficient for installed base is also within the same range as CSI models.

Robustness check for Model 2 shows similar results as Model 1 above. Complete robustness check results for Model 2 are presented in Appendix B.

Chapter 4: Consumer Discount Rate and the Expansion of Third-Party Owned Systems

This chapter explores the effects of third-party owned (i.e. leased) model[*] in opening up residential PV market to new adopters. As elaborated below, evidence from major adoption clusters in California show that growth in leasing adoption exhibits exponential characteristics while growth of customer owned system, shows a linear growth overtime.

4.1 DISCOUNT RATE AND CONSUMER DEMAND FOR RESIDENTIAL SOLAR PHOTOVOLTAIC

The three major barriers in the decision to purchase residential solar PV are high up-front cost, long payback time, and uncertainties associated with the long-term performance of the technology (Margolis *et.al*. 2006). At the time of adoption, potential adopters face an intertemporal choice of trading off between high upfront cost and the benefits that pay off over time. One prominent theory in characterizing consumer's behavior in such decision is the discounted-utility (DU) model proposed by Paul Samuelson (1937). The theory postulates that under an ideal condition a consumer's rational decision on intertemporal choice can be measured and described by a constant parameter, the discount rate. Under this simplified framework, consumer discount rate associated with residential solar PV can be broken down into two categories based on the adoption barriers – financial discount rate (that associated with the purchasing capability of the potential adopter) and information discount rate.

The net present value (NPV) is commonly used in appraising the value of capital investments. A simple NPV of a residential solar PV system is calculated based on the costs of the system and future savings resulting from the reduction in energy bills.

[*] In this chapter the terms third-party owned and leased systems are used interchangeably

Discount rate is applied to the expected benefits to determine the present value of future cash flow. The lower is discount rate, the higher the NPV and the more attractive solar PV installation become financially. To an extent, the financial discount rate is specific to each consumer who has a unique reaction to a given price depending on his or her beliefs and financial situations. Previous studies have shown that consumer's discount rate associated with energy durable goods vary inversely with income (Hausman 1979, Gately 1980).

Benthem, Gillingham, and Sweeney (2007) calculated the NPV based on subsidy policies, expected savings, maintenance costs, and other technical data of a "typical" system for a solar customer in California. They then modeled the overall consumer demand for solar PV as a function of NPV, market size, and diffusion overtime and showed that demand has grown with the increase in NPV of a system. In this model, the diffusion component indicates that demand increases as more systems are installed and consumers become more familiar with the technology (Benthem, et. al. 2007).

This suggests that the information component of the discount rate is a function of the installed base. This component captures the technology risks and performance uncertainties. If a consumer has limited knowledge about residential solar PV systems, he or she cannot anticipate what the costs and savings associated with owning the system will be. This is equivalent to saying that their information discount rate is high. In an area where there is high installed base of solar, consumers are more likely to be able to engage with previous adopters and gain more knowledge and familiarity with the technology. In so far as the diffusion is low, consumer's information discount rate will remain high.

4.2 The effect of third-party owned model on consumer discount rate

Presumably, the leasing model reduces, if not completely eliminates, the information component of a potential adopter's discount rate. Thus, once the leasing option is made available to customer, the net present value associated with adoption under third-party ownership is largely determined by the expected future savings from electricity generated on-site and consumer's financial discount rate. Third-party PV companies install and operate solar PV system on the customer's premises. The companies maintain ownership of the systems and let the customer either lease the system at a fixed monthly cost or buy the electricity produced by the system thorough a power purchase agreement (PPA). Under these arrangements, third-party ownership can reduce or eliminate the upfront cost of installation; thus, changing the NPV of system adoption. By removing the high capital requirement, third-party systems make adoption possible to a new set of customer who may have been unwilling or unable to finance a system purchase.

Information discount rate is essentially eliminated with the leasing model. Since the systems are owned and operated by the companies, customers are unburdened from any system repair and maintenance costs. Third party ownership allow customer to take advantage of solar PV benefits while avoiding the technology risks. The leasing model has an effect of lowering the overall discount rate, thus increasing the net present value of residential PV adoption.

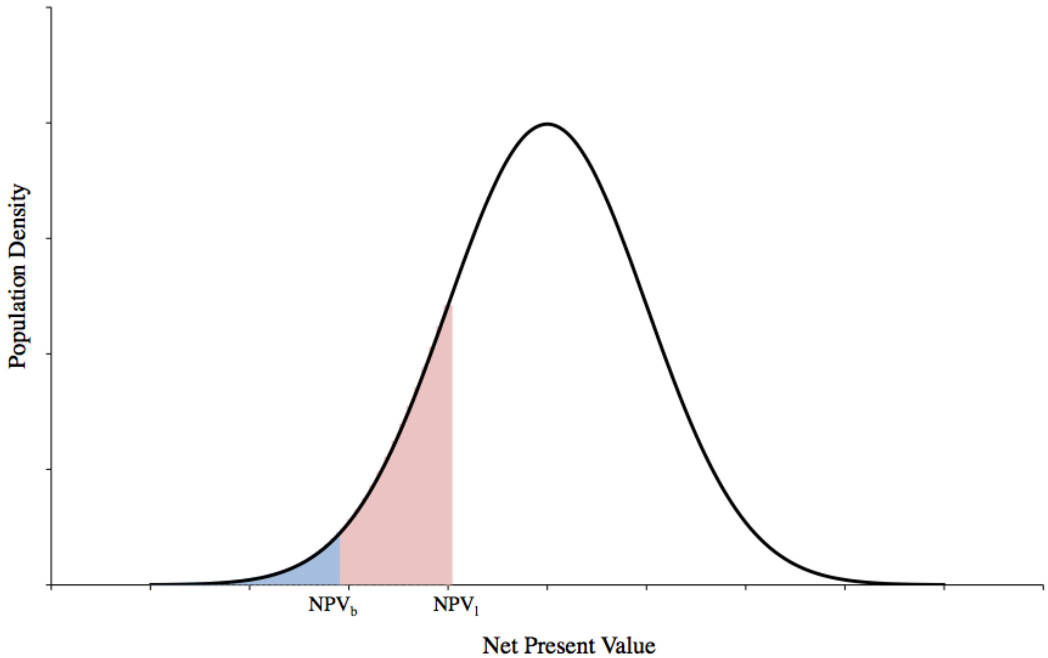


Figure 4.1: Relationship between net present value and adopter population under a normal distribution assumption

Figure 4.1 illustrates the relationship between NPV and the number of potential adopters. Assume that under a normal population distribution the NPV associated with system purchase is located at NPV_b. The blue shaded area represents the population who are able to adopt the technology at that NPV due to a combination inherently high individual's financial and information discount rates. I emphasize that the leasing option reduces the discount rate by an amount that increases the NPV for adoption to a higher NPV_l. The difference between NPV_b and NPV_l significantly expands the number of potential adopters as shown by the larger shaded area in red. This increased adopter population is exponential so we should expect an exponential growth in the leasing of PV system.

4.3 Third-party systems in California

In August 2008, the California State Assembly passed a legislation exempting third-party PV solar companies from Public Utilities Commission's (PUC) regulatory authority. Prior to the ruling, third-party solar PV companies faced regulatory uncertainty on the use of the PPA model since under the previously existing law any entity that sold electricity to residential utility customer was required to register with the PUC and be regulated as an electric corporation. PUC regulatory requirements would add compliance and administrative costs to the companies making the PPA business model less economically attractive. The law created an exception for third-party owners of solar generation from being defined electrical corporations. At the end of 2008, share of third-party owned system was around 7.5% of the market in California, by the end of second quarter 2011, third-party systems made up about 20% of the residential PV capacity installed in California.

4.4 Cluster analysis

In this chapter, analysis of adoption treads is conducted at a cluster level. Here a cluster is defined as an area within 30 miles radius of a major adoption city. Cluster-level analysis is used to control for any geographical distance factors that may contribute to differences in adoption trends and characteristics such as timing of adoptions and system sizes. The left heat-map in Figure 4.2 shows the cumulative installed capacity of residential solar PV and the locations of adoption clusters analyzed in this chapter. The heat-map on the right shows the cumulative installed capacity of third-party systems in California. Cluster-level installations are summarized in Table 4.1.

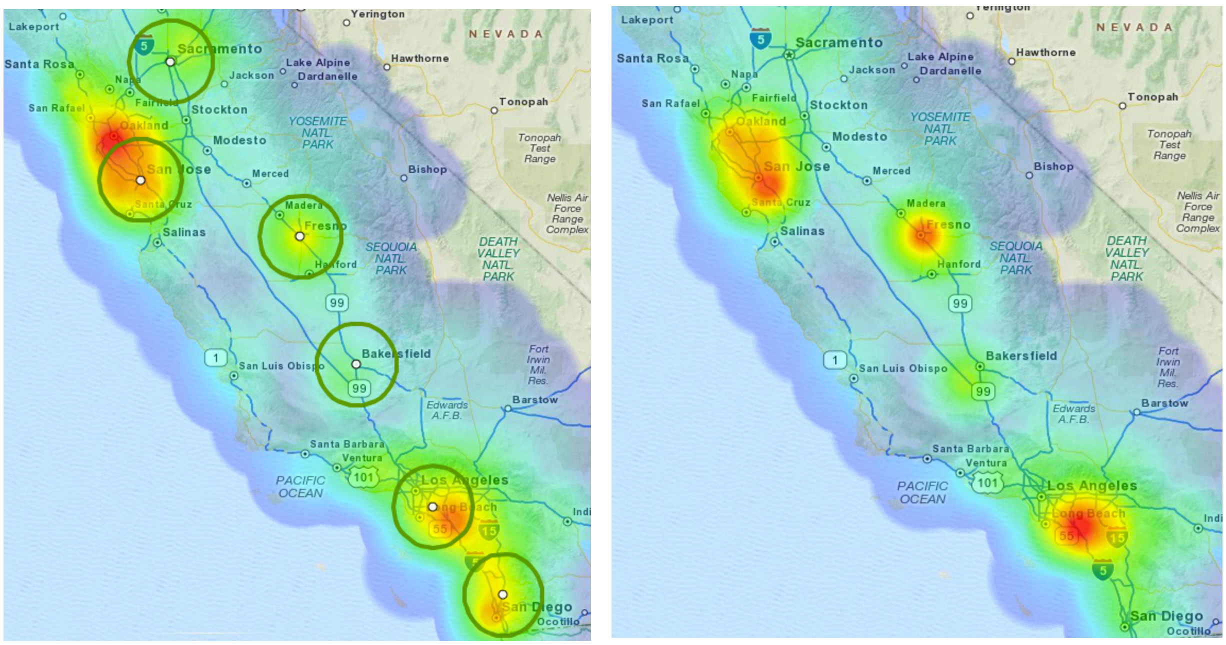


Figure 4.2: Left - Heat map of system installations and locations of adoption clusters as defined in this work.
Right - Heat map of third-party system installations.

	Total Installed Capacity	Average System Size (kW)	Number of systems
San Jose	29410	4.15	7150
San Diego	24560	4.35	4898
L.A.	19590	3.98	5821
Fresno	12230	5.43	2256
Sacramento	10003	4.66	2153
Bakersfield	5520	5.49	1006

Table 4.1: Adoption summary for San Jose, San Diego, Los Angeles, Fresno, Sacramento, and Bakersfield clusters.

4.5 TRENDS IN SYSTEM ADOPTIONS

Figures 4.3 – 4.8 plot the cumulative installed capacity of customer-owned (i.e. "bought") systems overtime in the different adoption clusters identified in Figure 4.2 and Table 4.1. The horizontal axis shows the date in which installations were completed and the vertical axis shows the cumulative installed capacity in kW. Installed system sizes are broken down into 0-3 kW, 3-5 kW, 5-7 kW, 7-9 kW, and larger than 9 kW categories to show the system size preferences of adopters in each clusters.

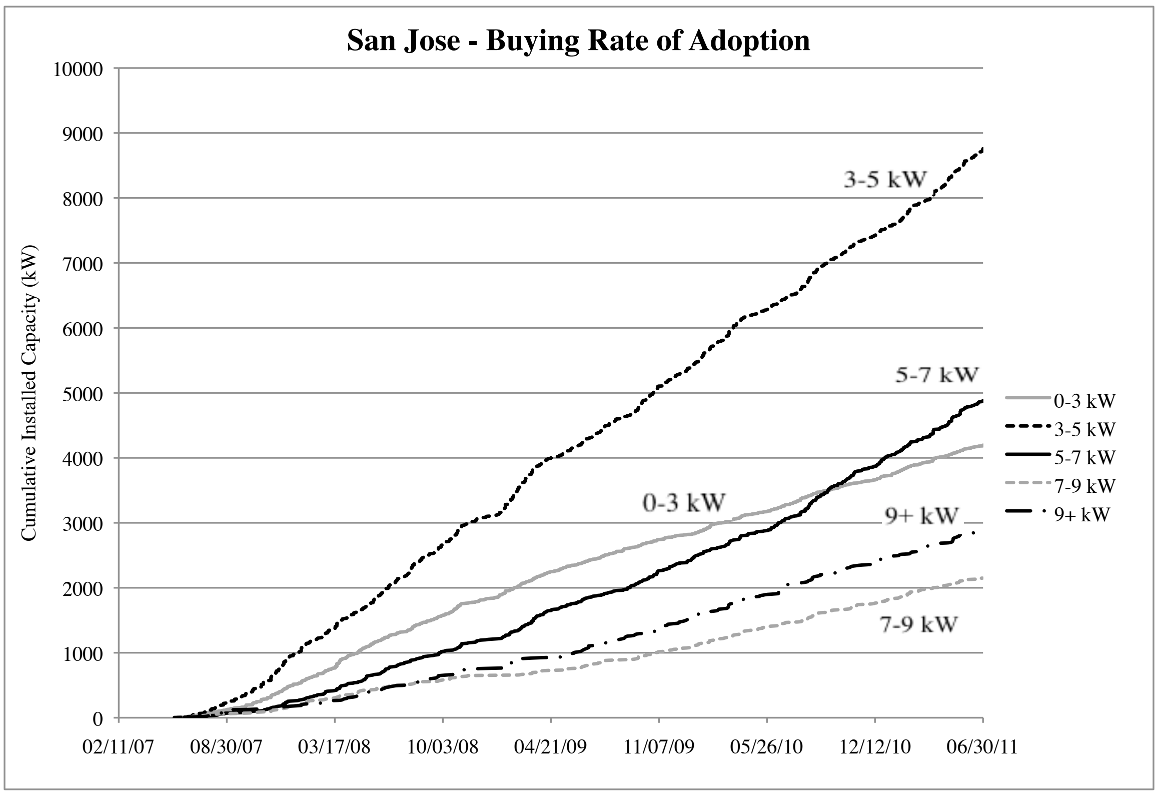


Figure 4.3: Growth of customer-owned systems by system size in San Jose.

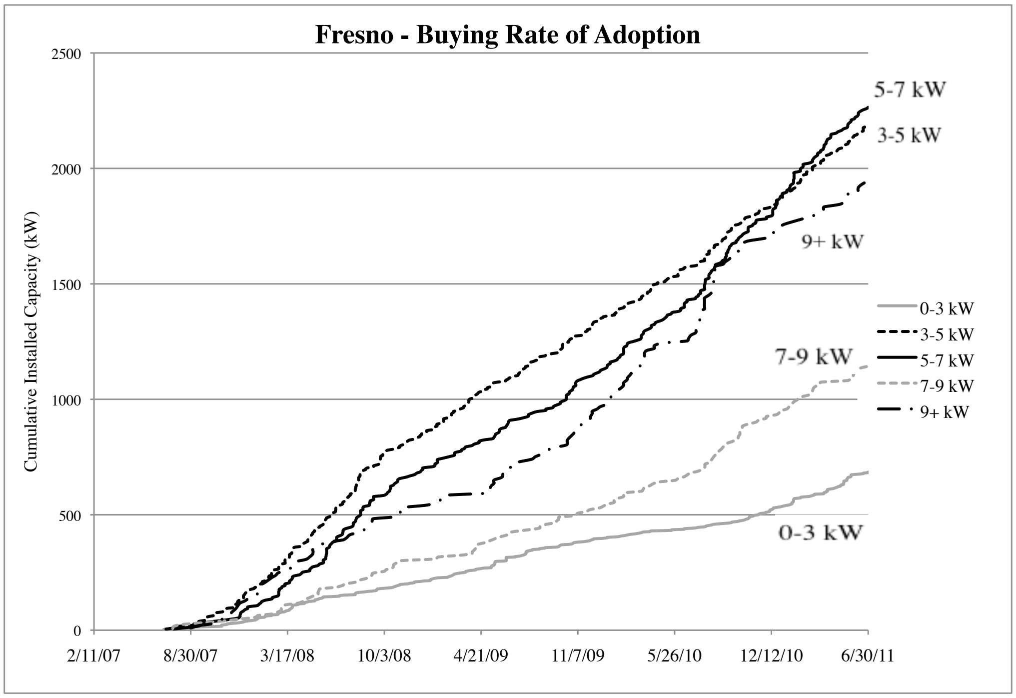


Figure 4.4: Growth of customer-owned systems by system size in Fresno.

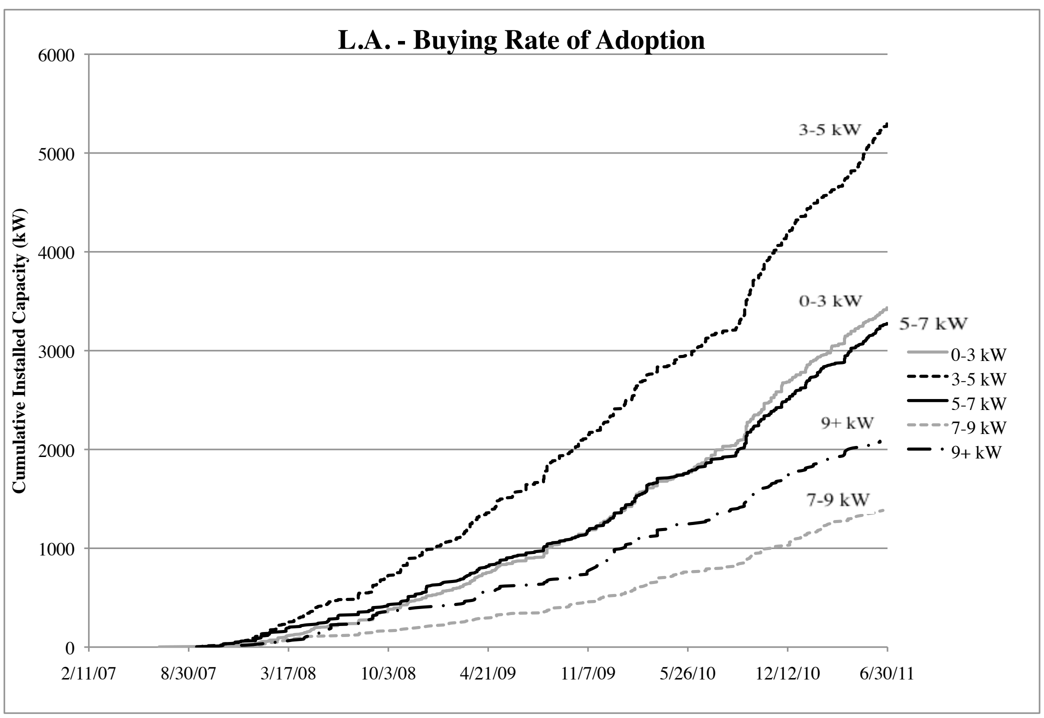


Figure 4.5: Growth of customer-owned systems by system size in Los Angeles.

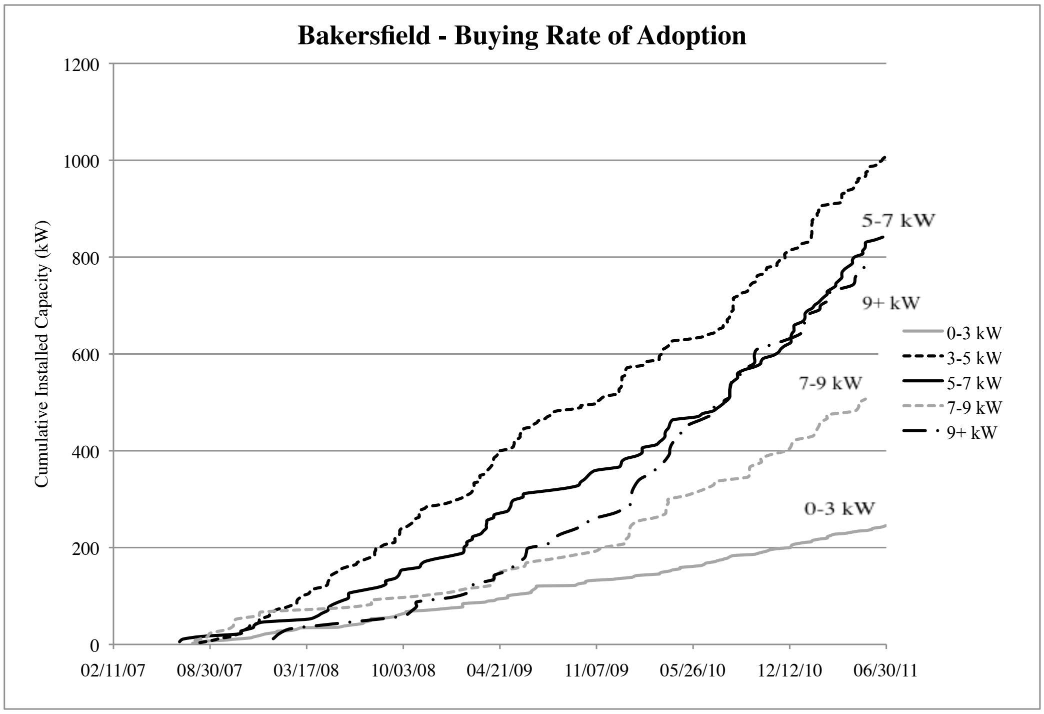


Figure 4.6: Growth of customer-owned systems by system size in Bakersfield.

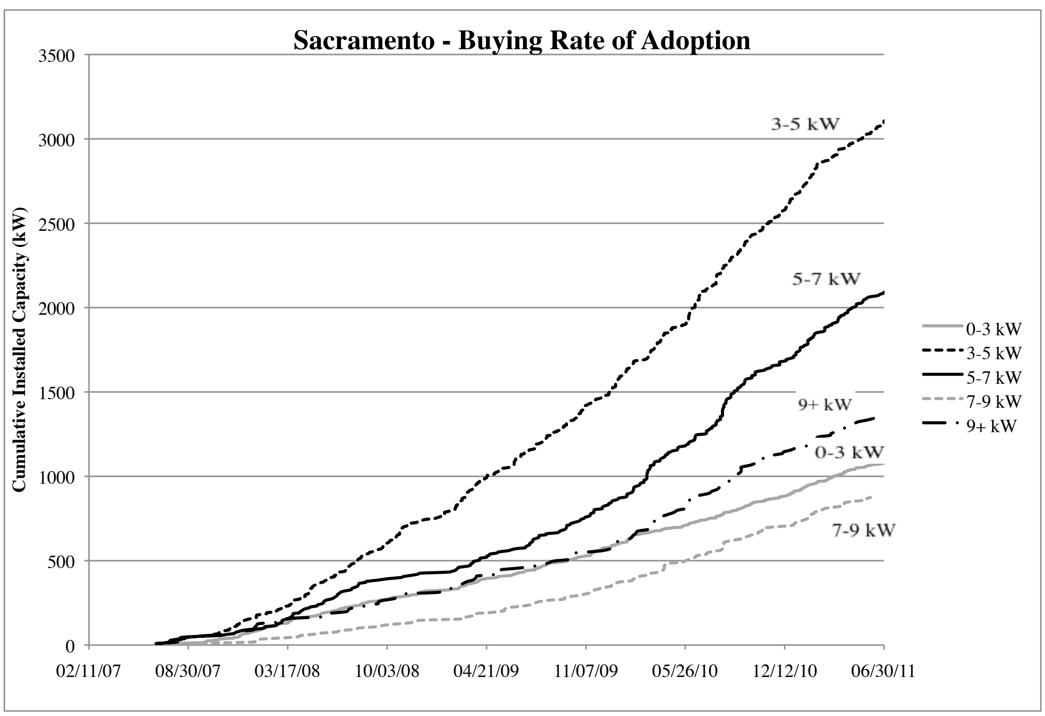


Figure 4.7: Growth of customer-owned systems by system size in Sacramento.

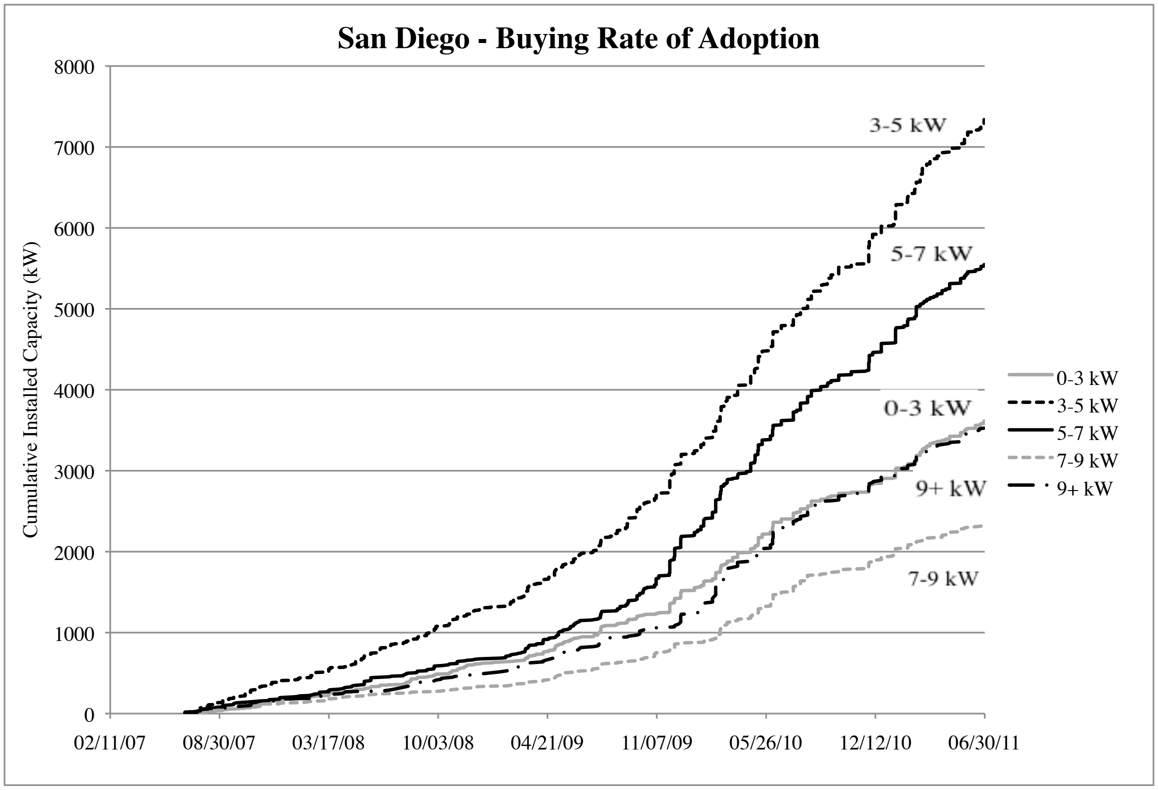


Figure 4.8: Growth of customer-owned systems by system size in San Diego.

Figures 4.3 - 4.7 illustrate the systematic property in the growth of adoption for customer-owned systems. In every cluster, except San Diego (Figure 4.8), growths of adoption for all system size categories display strongly linear characteristics with growth rate remaining relatively constant through out the study period.

The exponential growth characteristic in San Diego cluster is an anomaly in the analysis. While other clusters such as Los Angeles and Sacramento show some evidence of exponential growth for certain size systems, the overall adoption profiles are generally linear. A possible explanation for the discrepancy in the San Diego cluster is related to the CSI MW rebated allocated to each utility service territory. The CSI rebate level decreases in step when a certain MW target is reached. The MW targets vary according to utility territory where each utility receives a different amount of MW worth of rebates.

Under this scheme, a utility with smaller allocation of MW will move through the rebate steps faster than the others even though they may experience relatively similar rate of adoption. Table 4.2 shows the MW available for each step by utility territory. The shading are in Table 4.2 show the current step as of April 30, 2012.

	MW Allocation in Step		
Rebate Step	PG&E	SCE	SDG&E
1	0	0.1	0
2	10.1	10.6	2.4
3	14.4	15.2	3.4
4	18.7	19.7	4.4
5	23.1	24.3	5.4
6	27.4	28.8	6.5
7	31	32.6	7.3
8	36.1	38	8.5
9	41.1	43.3	9.7
10	50.5	53.1	11.9

Table 4.2: CSI program incentive MW available by step and utility territory.[15]

As shown in Table 4.2 above, SDG&E has the lowest MW allocated for its customers. San Diego cluster is served by San Diego Gas & Electric (SDG&E) while the other five clusters are served by either Pacific Gas and Electric (PG&E) or Southern California Edison (SCE). A hypothesis to why San Diego cluster has a different growth profile than other clusters is that third-party solar PV companies chose to focus their efforts on the bigger markets (PG&E and SCE) as they can install more systems at higher rebate levels than in SDG&E territory. One other possible reason is that since the rebate steps are changing quickly relative to the other two utilities, the scarcity of available

15 http://www.csi-trigger.com/dataAnnex.aspx

incentives shortens the decision-making time for customers in SDG&E territory resulting in faster diffusion profile.

In contrast to the linear characteristics of customer-owned systems, third-party owned installations exhibit exponential growth rate in all clusters. Figure 4.9 – 4.14 show the growth in adoption for third-party owned systems.

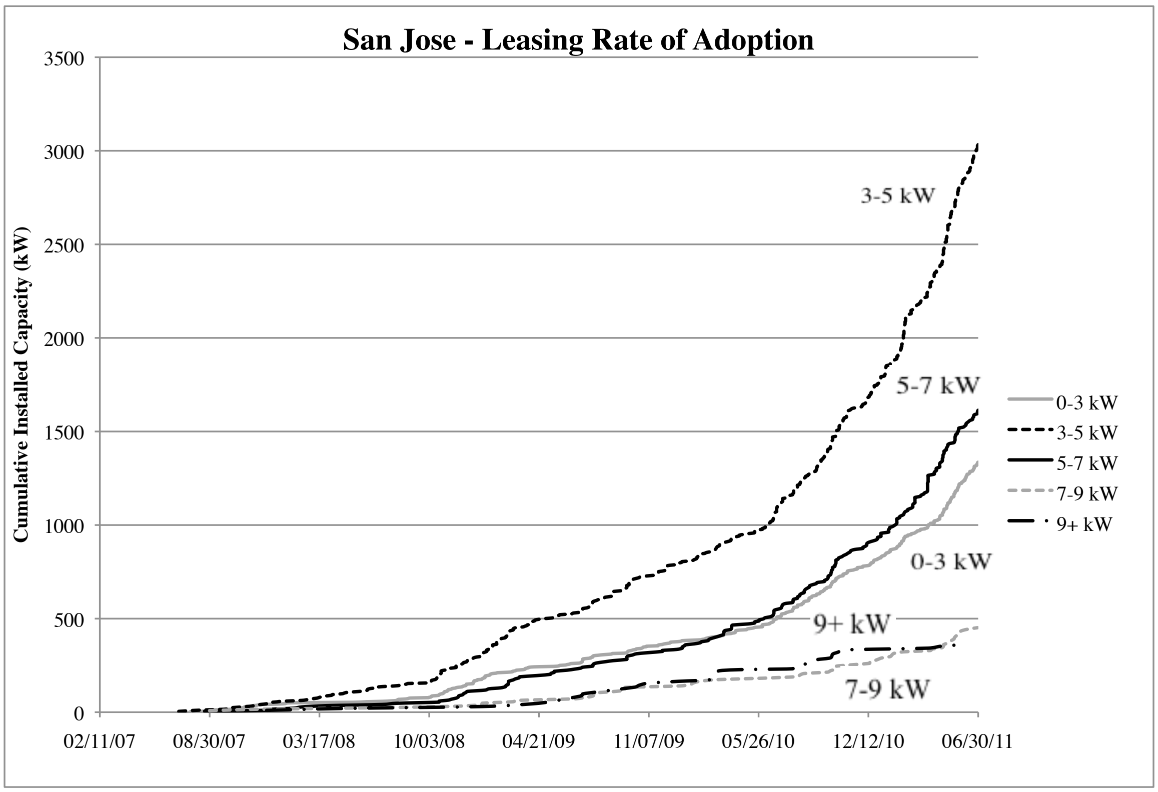


Figure 4.9: Growth of third-party owned systems by system size in San Jose.

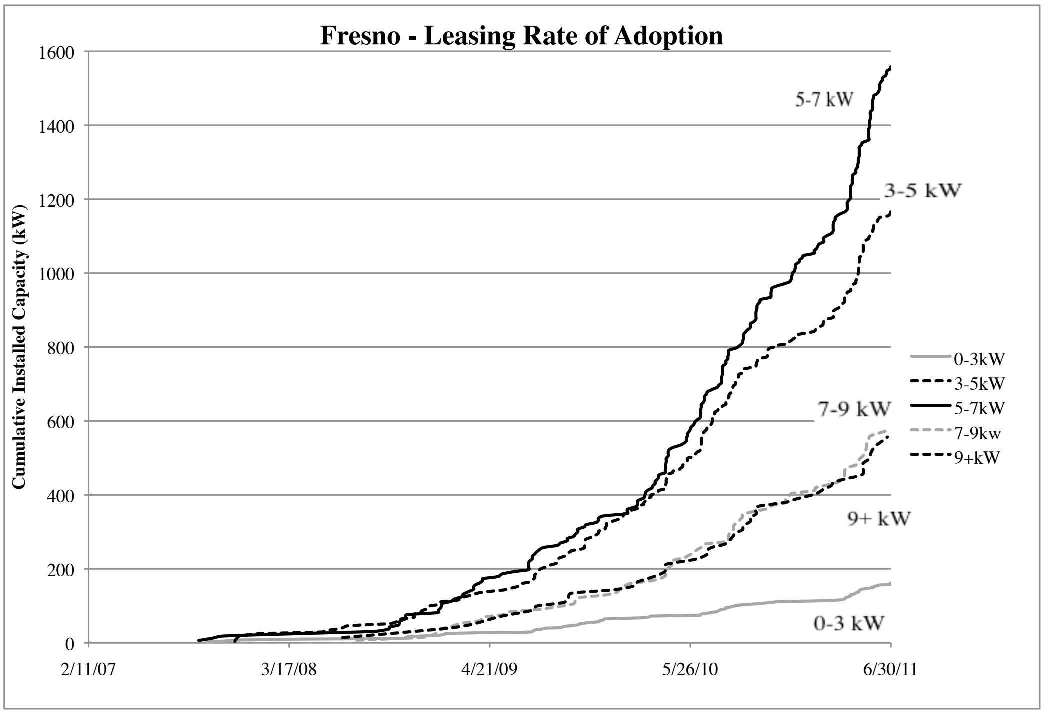


Figure 4.10: Growth of third-party owned systems by system size in Fresno.

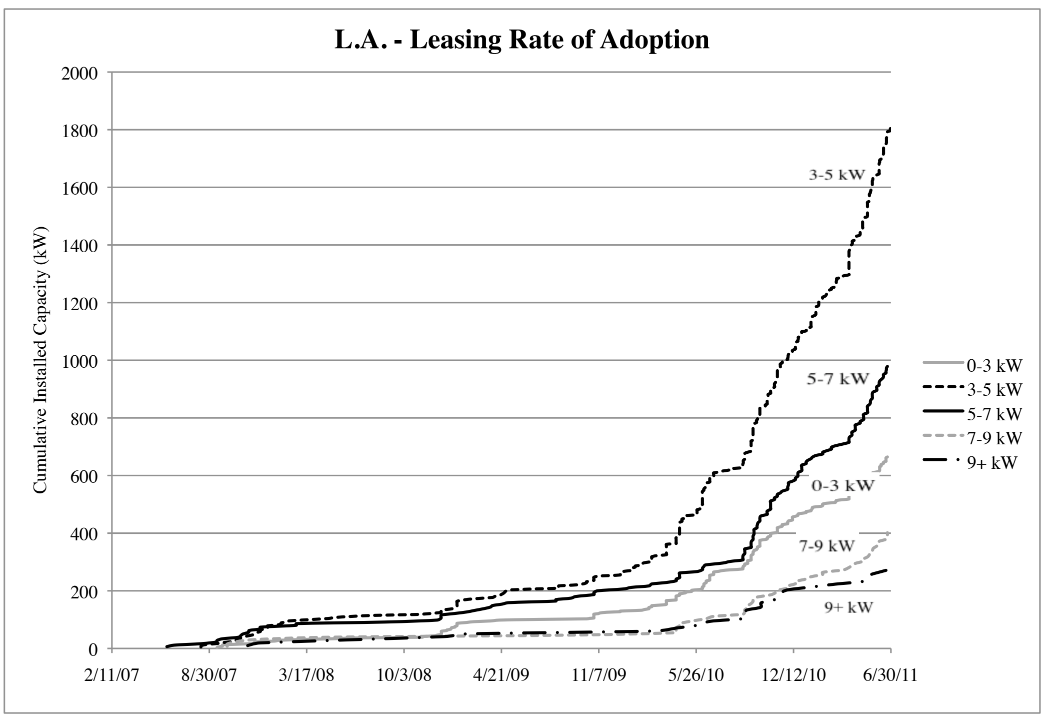


Figure 4.11: Growth of third-party owned systems by system size in Los Angeles.

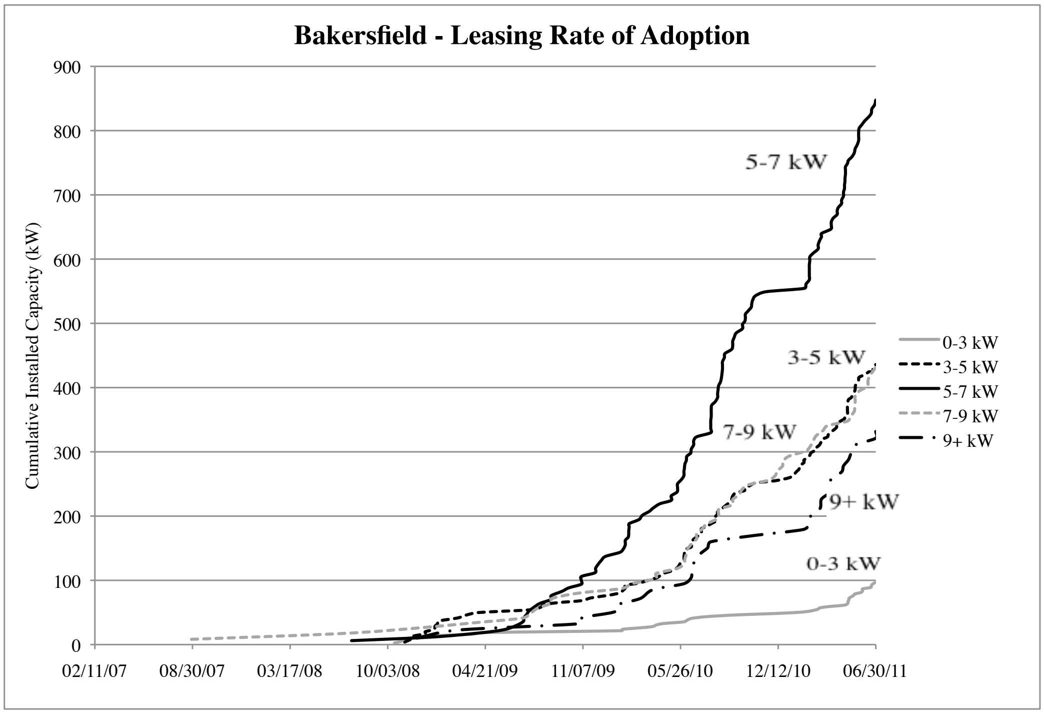


Figure 4.12: Growth of third-party owned systems by system size in Bakersfield.

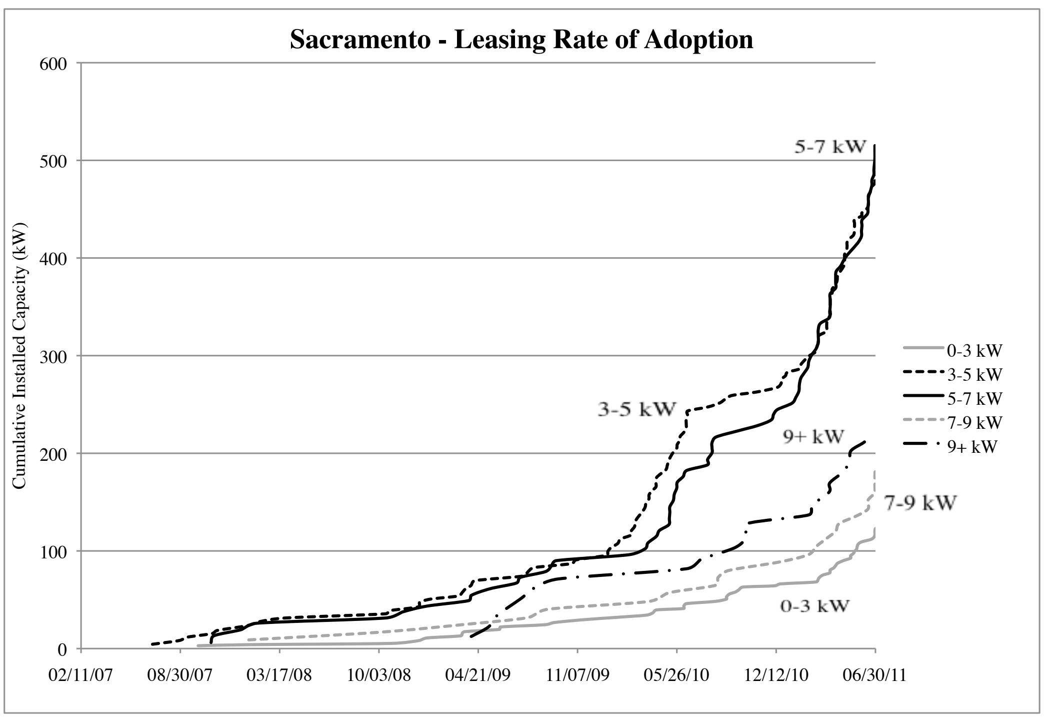


Figure 4.13: Growth of third-party owned systems by system size in Sacramento.

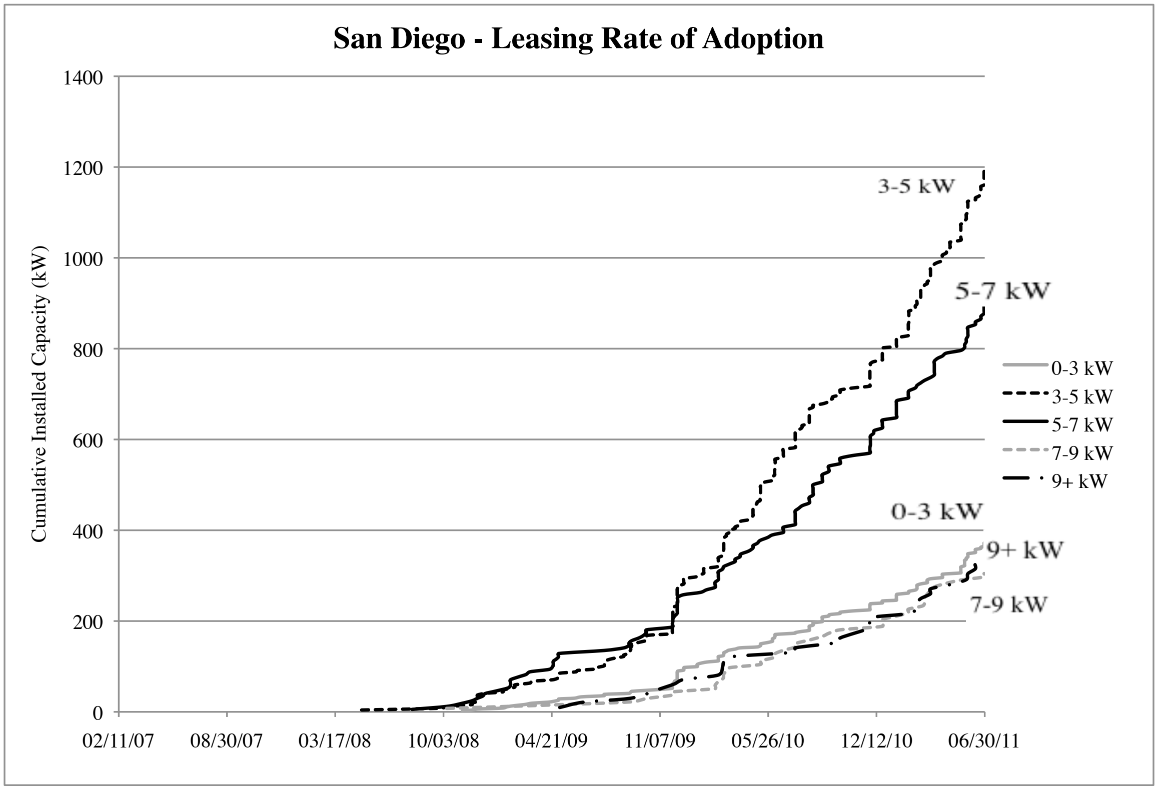


Figure 4.14: Growth of third-party owned systems by system size in San Diego.

In every cluster, third-party installations began growing rapidly after 2008, which coincide with the legislative action classifying third-party solar companies as non-electric corporations (see Section 4.3). Growths for most system size categories show strong exponential trends compared to growths of customer-owned systems. The systematic difference as compared with customer-owned systems illustrates how the third-party owned model has opened up the market for new potential adopters.

The reasons are twofold. First, third-party option makes adoption more financially attractive to a much larger population of potential adopters. Second, to a smaller extent, peer effects associated with third-party adoption may have broader consequence than peer effects from customer-owned systems.

With regard to the first reason, recall from Figure 4.1, the number of potential adopters increases rapidly as the NPV of adoption move to the right along the population density curve. The normal distribution function is represented by:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

where σ is the standard deviation and μ is the mean, which is located at the peak of the distribution. The exponential term increases as x moves toward the mean. Thus, for every unit increase in NPV, the portion of the population for which NPV is positive for adopting PV increases exponentially, resulting in larger market expansion.

4.6 INSTALLED BASE AND PEER EFFECTS

As previously discussed, third-party option eliminates the technology risks for consumers. To the extent that interpersonal networks play a role in adoption decision, the conversations between potential leased systems adopter and previous adopters of the systems would focus more on the financial benefits of the technology, which are immediate and quantifiable (monthly savings) rather than technology risks. On the other hand, potential adopters who are considering system purchase need to seek out information on technology performance, which include unpredictable and costly elements such as system breakdown and inverter replacement. For leaser, uncertainties in system performance are further reduced as third-party solar contractors generally provide the estimated savings for consumer prior to installation. Consequently, the search cost associated with third-party system adoption is much lower consisting of mostly financial information. The interactions between would be leaser and previous adopters are shallower making the peer effects spread quicker as potential adopters have less reliance on the experiences of previous adopters beyond the basic introduction to the technology.

4.7 INCOME AND SYSTEM SIZE

Presumably within a limited geographic area people who own larger homes are more affluent. For example, they may have higher household income or greater access to capital to afford the higher mortgage. As the system size is generally limited physically by the space available to accommodate solar panels it follows that larger solar PV systems are installed in bigger houses. In so far as these assumptions hold, system size can be used as a proxy for income distribution within a cluster.

Figures 4.15 – 4.18 plot the ratio of third-party capacity to total installed capacity over time for San Jose, Fresno, Bakersfield, and San Diego clusters. The x-axis shows the completion dates and the y-axis shows the ratio of cumulative third-party owned capacity and the total cumulative installed capacity (customer-owned and third-party system). The ratio represents the market penetration of third-party owned model in the solar PV market.

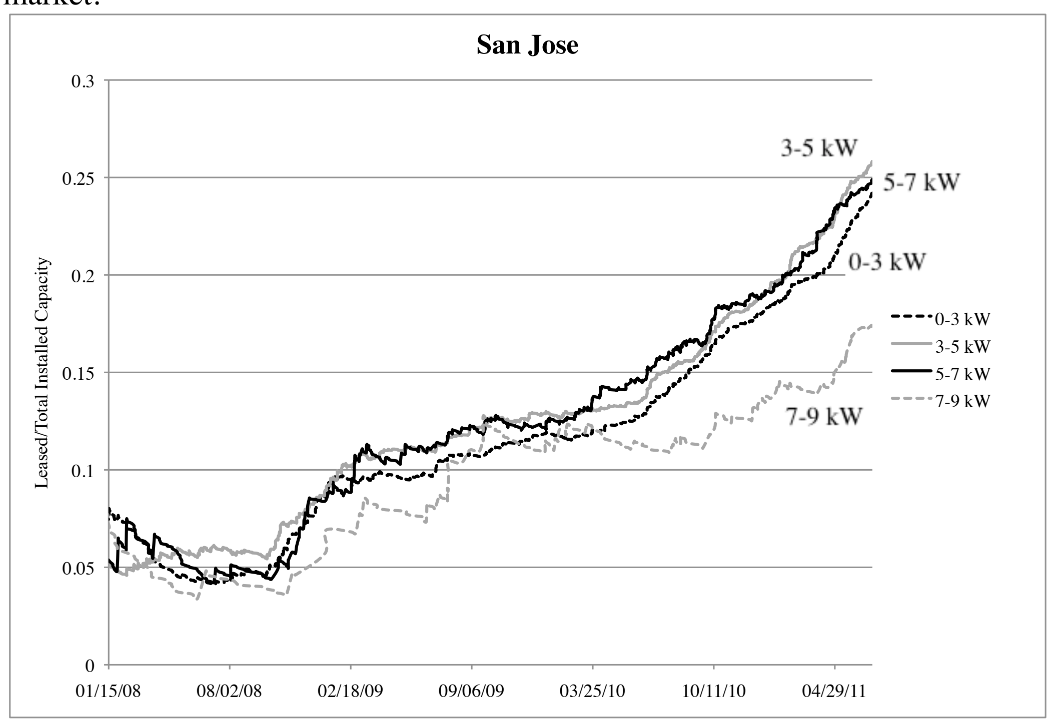


Figure 4.15: Third-party systems market penetration in San Jose.

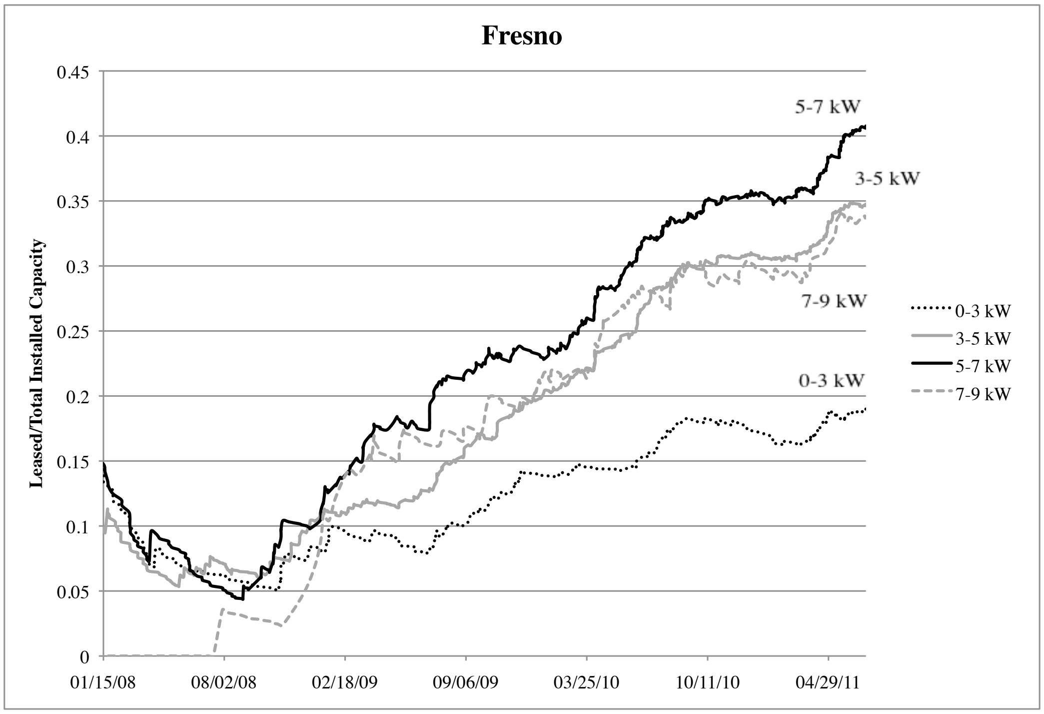


Figure 4.16: Third-party systems market penetration in Fresno.

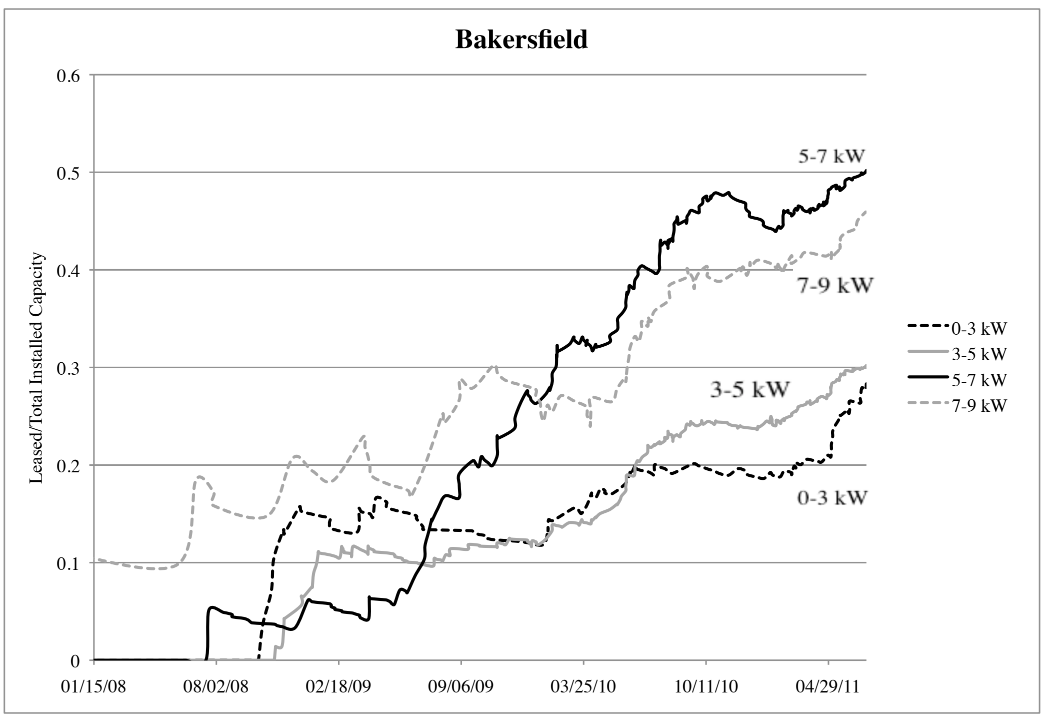


Figure 4.17: Third-party systems market penetration in Bakersfield.

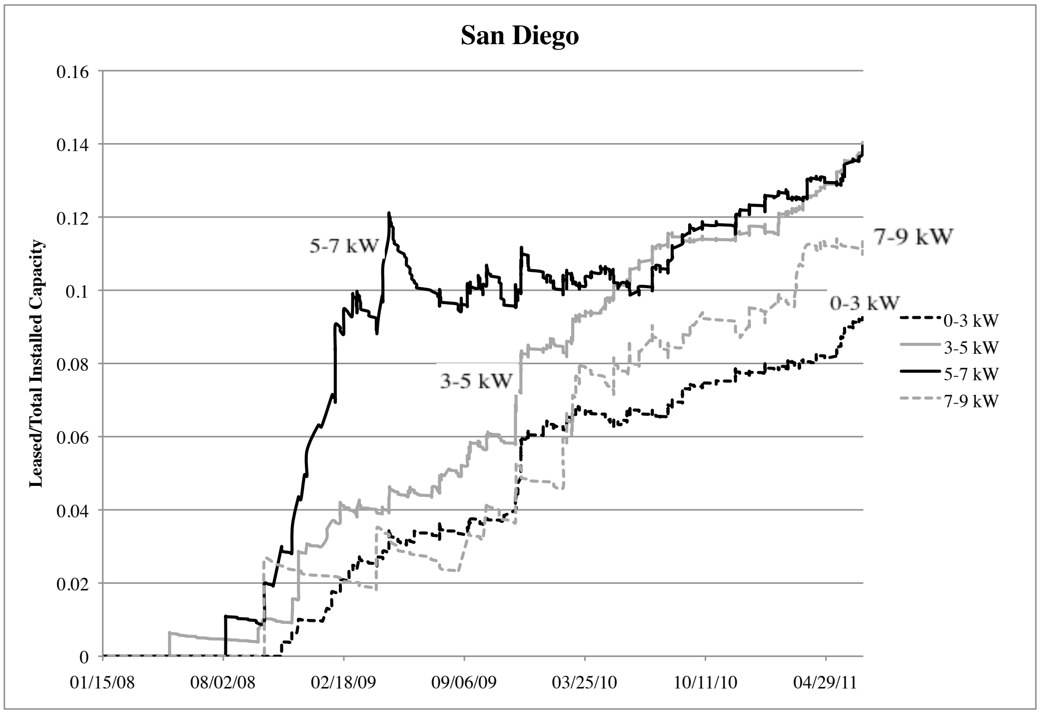


Figure 4.18: Third-party systems market penetration in San Diego.

Figure 4.15 – 4.18 show the market penetration of third-party owned system broken down by system size. These results show an increasing market share for all system size categories across every cluster. Given that third-party owned systems provide greater affordability (by increasing NPV), we should expect that population associated with lower income demographics would opt to adopt a lease system. If leased systems are adopted mostly by people with lower income, then the market penetration for third-party owned systems should be higher for smaller size systems. However, with one exception[16], the results show no systematic bias toward smaller system sizes.

[16] One exception where larger houses show a preference for buying is in the San Jose cluster (Figure 4.15) where system 7-9 kW size category has lower market penetration. In Fresno cluster (Figure 4.16) the smallest system size category (0-3 kW) market penetration shows that smaller home in this area has a stronger preference for buying than leasing.

Although one of the main premises for the growth of third-party owned system is that it reduces the financial discount rate for potential adopters that lead to greater affordability for population associated with lower income demographics, the results show no systematic bias toward smaller system size. This suggests that there is no specific relationship between income demographics and market penetration of third party systems.

Plots for Los Angeles and Sacramento clusters are shown in Appendix C.

4.8 Policy Implication

Third-party owned systems were adopted prior to PUC ruling on the exemption of third-party solar companies from being regulated as electric corporation. Due to this regulatory uncertainty, third-party owned systems installation remained relatively stagnant while customer-owned systems experienced sustained growth. Our analysis of the installation trends show third-party systems growing exponentially and gaining market share soon after the regulatory barrier was removed in August 2008. Third-party business model reduces financial and technology-related barriers for consumers thus, expanding the solar PV market into a significantly larger population base. Consequently, policies that remove non-market barriers discouraging third-party solar PV companies from competing in the market have a potential to expedite and expand solar PV adoption. Various states have found legislative and regulatory solutions around the issue. However, barriers remain in regions around the country specifically in areas where electricity market is regulated or under a monopoly utility. The City of Austin is a good example of this.

Chapter 5: Conclusion

In this thesis I developed a spatial-temporal model that estimates the peer effects and cost drivers in the diffusion of solar PV at the zip-code level. The results reveal significant and positive installed base effects in the rate of future adoption. The cost-to-customer reduction is negative and significant at the state level. The impact of peer effects in inducing new adoption is larger in zip codes with higher overall adoptions.

In the second part of the thesis I documented systematic patterns in the growth of residential solar PV adoption in different markets in California. The exponential characteristics in the growth of third-party systems point to a market expansion into a new set of potential adopters. Increase market share of third-party owned adoptions in all system sizes suggest no underlying differences in income demographic between residence-owned and third-party owned adopters. Rather, our results suggest that the "new adopters" unleashed on the leasing model had higher information costs (associated with technology risk) for the bought model. But as the leasing model eliminates those costs almost entirely, these potential adopters become activated and ready for adoption.

Future Research

As peer effects occur because of several factors, social learning arising from increased installed base may be complimented by social norms such as environmental concerns and image motivations. Estimation of installed based component of peer effects can be improved by controlling for the presence of prescriptive social influences.

Analysis of consumer discount rate points to the importance of third-party owned model in the expansion of solar PV market. Further work to explore the growth of third-party owned systems in other markets (e.g. commercial customer and other regions) may also provide insights into quantifying the impacts of third-party companies in the diffusion of solar PV technology.

Appendix A

Table A.1 Summary statistics for socio-demographic variables, 2007

Variable	Obs	Mean	Std. Dev.	Min	Max
Median Household Income	1621	60514.52	28499.24	8760	375000
Per Capita Income	1621	30071.76	16697.66	3826	118820
Household Income Base	1621	7735.332	6900.122	3	32848
Household Income <$25k	1621	22.11357	12.37207	0	86.9
Houselhold Income $25k - $50k	1621	23.2971	7.897873	0	66.7
Household Income $50k - 100k	1621	30.84392	6.995501	0	58.1
Household Income $100k - 150k	1621	13.06336	6.48158	0	33.3
Household Income >$150k	1621	10.68402	11.33896	0	100
Owner Occupied Housing Base	1621	4530.633	4181.16	2	23670
Owner Occupied Income <$50k	1621	2.915669	4.688449	0	54.7
Owner Occupied Income $50k - $90k	1621	2.249537	3.249183	0	37.3
Owner Occupied Income $90k - $175k	1621	6.677545	8.755601	0	61.7
Owner Occupied Income $175k - $400k	1621	32.12535	23.29525	0	100
Owner Occupied Income >$400k	1621	56.03078	30.59106	0	100
Median Owner Occupied Home Value	1621	514595.1	261476.4	29167	1000001

Table A.2 Summary statistics for socio-demographic variables, 2009

Variable	Obs	Mean	Std. Dev.	Min	Max
Median Household Income	1628	61801.84	29647.59	8965	348129
Per Capita Income	1628	29307.02	16289.39	4826	153783
Household Income Base	1628	7778.512	6874.376	3	32352
Household Income <$25k	1628	20.91517	12.08033	0	85.7
Houselhold Income $25k - $50k	1628	23.54509	8.489884	0	63.4
Household Income $50k - 100k	1628	32.97082	7.83451	0	75
Household Income $100k - 150k	1628	12.29613	7.408786	0	35.6
Household Income >$150k	1628	10.27101	12.09157	0	100
Owner Occupied Housing Base	1628	4402.877	4036.965	2	18754
Owner Occupied Income <$50k	1628	4.843305	7.508364	0	71.9
Owner Occupied Income $50k - $90k	1628	4.209029	6.891618	0	57.9
Owner Occupied Income $90k - $175k	1628	16.91781	18.70979	0	100
Owner Occupied Income $175k - $400k	1628	38.2809	22.37981	0	100
Owner Occupied Income >$400k	1628	35.74822	31.35659	0	100
Median Owner Occupied Home Value	1628	354529.5	221031.7	13571	1000001

Appendix B

Results of robustness check for zip code fixed effects Model 2.

	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|
Cost-to-customer	-0.06741	<.0001	-0.07939	<.0001	-0.04386	0.0202
Installed based	0.003855	<.0001	0.004202	<.0001	0.01812	<.0001
Geography	PG&E		Santa Clara County		San Jose	
Number of zip codes	597		51		29	
R-Square	0.6545		0.4807		0.471	

	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|
Cost-to-customer	-0.12415	-0.12415	-0.12973	<.0001	-0.11152	-0.11152
Installed based	0.001483	0.001483	0.020527	<.0001	0.031781	0.031781
Geography	SCE		Orange County		Huntington Beach	
Number of zip codes	405		80		4	
R-Square	0.5238		0.4872		0.1426	

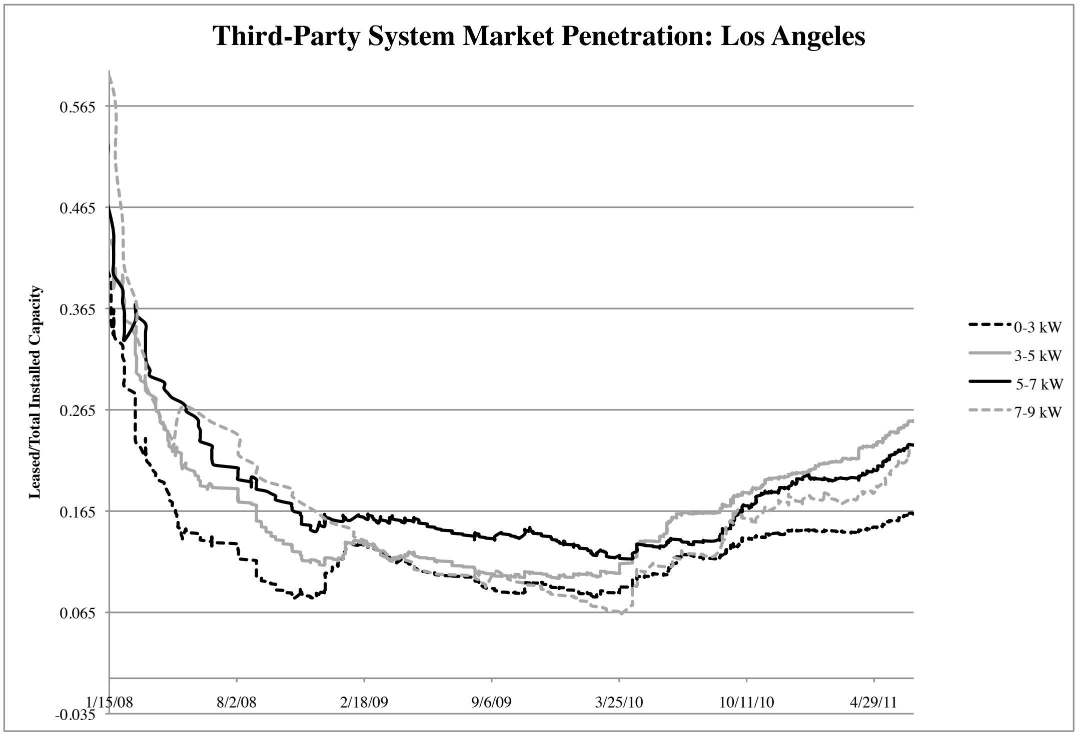
	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|
Cost-to-customer	-0.13894	<.0001	-0.14428	<.0001	-0.17036	<.0001
Installed based	0.006558	<.0001	0.00621	<.0001	0.004319	<.0001
Geography	SDGE		San Diego County		San Diego	
Number of zip codes	104		91		42	
R-Square	0.537		0.5389		0.5008	

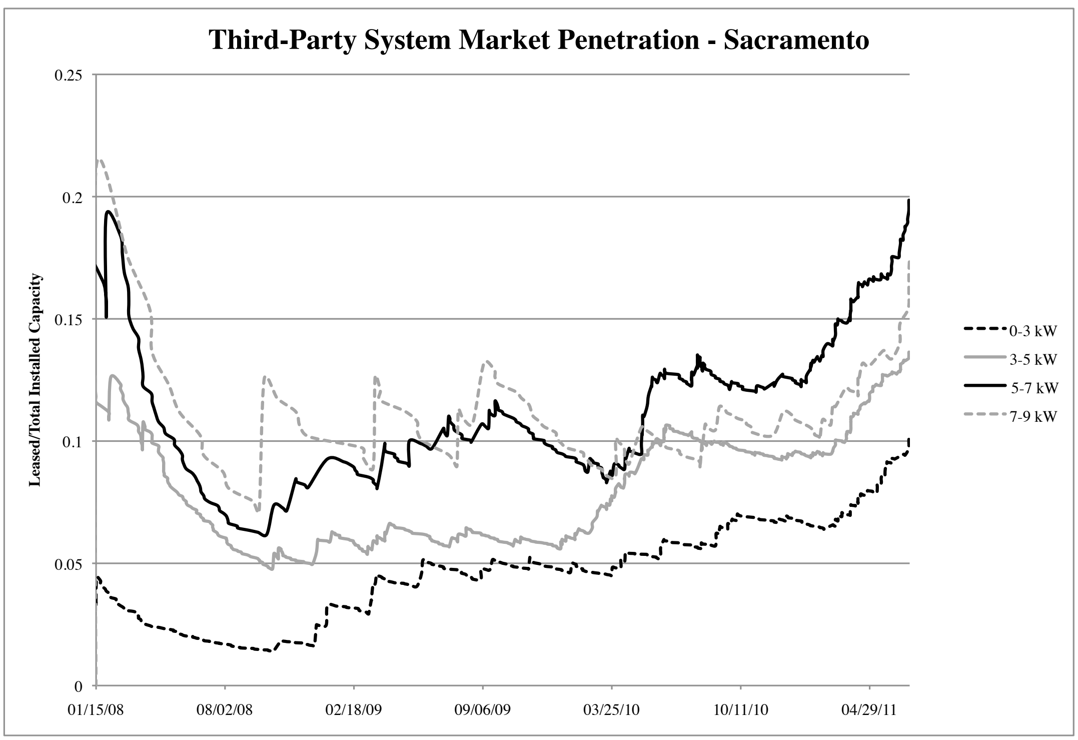
Table B.1: Parameter Estimates Results for utility, county, and city level models for Model 2.

	Estimate	Error	t Value	Pr > |t|	R-Square
Cost-to-customer	-0.04262	0.0108	-3.93	<.0001	
Installed base	0.005702	0.00189	3.01	0.0027	0.5671

Table B.2: Parameter Estimates Results for Austin data for Model 2.

Appendix C


Third-Party System Market Penetration: Los Angeles
Leased/Total Installed Capacity
0.565
0.465
0.365
0.265
0.165
0.065
-0.035
1/15/08
8/2/08
2/18/09
9/6/09
3/25/10
10/11/10
4/29/11
0-3 kW
3-5 kW
5-7 kW
7-9 kW


Third-Party System Market Penetration - Sacramento
Leased/Total Installed Capacity
0.25
0.2
0.15
0.1
0.05
0
01/15/08
08/02/08
02/18/09
09/06/09
03/25/10
10/11/10
04/29/11
0-3 kW
3-5 kW
5-7 kW
7-9 kW

References

Austin Energy. (2003, December 4). Austin Energy's 2003 Strategic Plan. Retrieved January 2012, from Austin Energy-Newsroom: http://www.austinenergy.com/about%20us/newsroom/Strategic%20Plan/strategicPlanningUpdate_2003.pdf

Benthem, A., Gillingham, K. & Sweeney, J. (2007). Learning-by-Doing and the Optimal Solar Policy in California. *Energy Journal,* 29 (3), 131-151

Bollinger, B., & Gillingham, K. (2011). Peer Effects in the Diffusion of Solar Photovoltaic Panels. Working Paper, Stanford University.

California Public Utilities Commission. (2009, June). California Solar Initiative Annual Program Assessment. Retrieved November 2011, from: http://docs.cpuc.ca.gov/PUBLISHED/GRAPHICS/103173.PDF

California State Assembly. AB 2863, Leno. Independent solar energy producers: master-meter customers. 2008.

Durham, C., Colby, B., Longstreth, M. (1988). The Impact of State Tax Credits and Energy Prices on Adoption of Solar Energy Systems. Land Economic, 64 (4), 347-355.

Drury, E., Miller, M., Macal, C., Graziano, D., Heimiller, D., Ozik, J. & Perry, T. (2012). The Transformation of Sourthern California's Residential Photovoltaics Market through Third-party Ownership. *Energy Policy,* 42, 681-690.

EERE, U.S. Department of Energy, Energy Efficiency & Renewable Energy. (2009) Renewable Energy Data Book, DOE/GO-102010-3074, August 2010. from: http://www1.eere.energy.gov/maps_data/pdfs/eere_databook.pdf

Faiers, A., Neame, C., & Cook, M. (2006). The adoption of domestic solar-power systems: Do consumers assess product attributes in a stepwise process? *Energy Policy*, 35, 3418–3423.

Gately, D., (1980). Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables: Comments. *The Bell Journal of Economics,* 11 (1), 373-374.

Geroski, P.A. (2000). Models of technology diffusion. *Research Policy*, 29, 603-625.

Hart, D. (2009) Marking, Breaking, and (partially) remaking markets: State Regulation and Photovoltaic Electricity in New Jersey. Working Paper Series. MIT-IPC-Energy Innovation Working Paper 09-005.

Hausman, J.A., (1979). Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables. *The Bell Journal of Economics,* 10 (1), 33-54.

Hoen, B., Wiser, R., Cappers, P. & Thayer, M. (2011). An Analysis of the Effects of Residential Photovoltaic Energy Systems on Home Sales Prices in California. Lawrence Berkeley National Laboratory. From: http://eetd.lbl.gov/ea/emp/reports/lbnl-4476e.pdf

Iyengar, R., Van den Bulte, C. (2011). Opinion Leadership and Social Contagion in New Production Diffusion. *Marketing Science*, 30 (2), 195-212.

Libby, L. (2011, February 23). Austin Energy Solar Programs. Presentation at the University of Texas at Austin . Austin.

Margolis, M., Denholm, P. (2007). Evaluating the limits of solar photovoltaics (PV)in traditional electric power systems. *Energy Policy*, 35, 2852-2861.

McEachern, M., Hanson, S. (2008). Socio-Geographic Perception in the Diffusion of Innovation: Solar Energy Technology in Sri Lanka. *Energy Policy,* 36 (7), 2578-2590.

Narayanan, S. and Nair, H. (2011), Estimating causal installed-base effects: A biascorrection approach. Stanford Graduate School of Business Research Paper Series No. 2076.

NREL National Renewable Energy Laboratory. (2009). Breakeven Cost for Residential Photovoltaic in the United States: Key Drivers and Sensitivities, December 2009. from: http://www.nrel.gov/docs/fy10osti/46909.pdf

Rogers, E. (2003). *Diffusion of Innovations*. New York: Free Press.

Rothfield, E. (2010). Solar Photovoltaic Installation in California: Understanding the Likelihood of Adoption Given Incentives Electricity Pricing and Consumer Characteristics. Duke University.

Samuelson, P. (1937). A Note on Measurement of Utility. *The Review of Economic Study,* 4 (2), 155-161.

Schelly, C. (2010). Testing Residential Solar Thermal Adoption. *Environment and Behavior,* 42 (2), 151-170.

SEIA. (2009). Solar Energy industries Association, US Solar Industry Year in Review 2009, from: http://seia.org/galleries/default-file/2009%20Solar%20Industry%20Year%20in%20Review.pdf

Shum, K., Watanabe, C. (2007). Towards a local learning (innovation) model of solar photovoltaic deployment. *Energy Policy*, 36, 508-521.

Stern, P.C. (2000). Toward a Coherent Theory of Environmentally Significant Behavior. *Journal of Social Issues*, 56 (3), 407-424.

Wiser, R., Barbose, G. & Darghouth, N. (2011). Tracking the Sun IV A Historical Summary of the Installed Cost of Photovoltaic in the U.S. from 1998 to 2010. *Lawrence Berkeley National Laboratory*.

Wiser, R., Barbose, G., Peterman, C. & Darghouth, N. (2009). Tracking the Sun II The Installed Cost of Photovoltaic in the U.S. from 1998-2008. *Lawrence Berkeley National Laboratory*.